Loss Data Analytics

An open text authored by the Actuarial Community

Contents

Preface

Date: 02 May 2023

Book Description

Loss Data Analytics is an interactive, online, freely available text.

- The online version contains many interactive objects (quizzes, computer demonstrations, interactive graphs, video, and the like) to promote *deeper learning*.
- A subset of the book is available for *offline reading* in pdf and EPUB formats.
- The online text will be available in multiple languages to promote access to a *worldwide audience*.

What will success look like?

The online text will be freely available to a worldwide audience. The online version will contain many interactive objects (quizzes, computer demonstrations, interactive graphs, video, and the like) to promote deeper learning. Moreover, a subset of the book will be available in pdf format for low-cost printing. The online text will be available in multiple languages to promote access to a worldwide audience.

How will the text be used?

This book will be useful in actuarial curricula worldwide. It will cover the loss data learning objectives of the major actuarial organizations. Thus, it will be suitable for classroom use at universities as well as for use by independent learners seeking to pass professional actuarial examinations. Moreover, the text will also be useful for the continuing professional development of actuaries and other professionals in insurance and related financial risk management industries.

Why is this good for the profession?

An online text is a type of open educational resource (OER). One important benefit of an OER is that it equalizes access to knowledge, thus permitting a broader community to learn about the actuarial profession. Moreover, it has the capacity to engage viewers through active learning that deepens the learning process, producing analysts more capable of solid actuarial work.

Why is this good for students and teachers and others involved in the learning process? Cost is often cited as an important factor for students and teachers in textbook selection (see a recent post on the $400 textbook). Students will also appreciate the ability to "carry the book around" on their mobile devices.

Why loss data analytics?

The intent is that this type of resource will eventually permeate throughout the actuarial curriculum. Given the dramatic changes in the way that actuaries treat data, loss data seems like a natural place to start. The idea behind the name *loss data analytics* is to integrate classical loss data models from applied probability with modern analytic tools. In particular, we recognize that big data (including social media and usage based insurance) are here to stay and that high speed computation is readily available.

Project Goal

The project goal is to have the actuarial community author our textbooks in a collaborative fashion. To get involved, please visit our Open Actuarial Textbooks Project Site.

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Contributors

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Version

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You can also access pdf and epub (current and older) versions of the text in our Offline versions of the text.

For our Readers

We hope that you find this book worthwhile and even enjoyable. For your convenience, at our Github Landing site (https://openacttexts.github.io/), you will find links to the book that you can (freely) download for offline reading, including a pdf version (for Adobe Acrobat) and an EPUB version suitable for mobile devices. Data for running our examples are available at the same site.

In developing this book, we are emphasizing the online version that has lots of great features such as a glossary, code and solutions to examples that you can be revealed interactively. For example, you will find that the statistical code is hidden and can only be seen by clicking on terms such as

We hide the code because we don't want to insist that you use the `R` statistical software (although we like it). Still, we encourage you to try some statistical code as you read the book – we have opted to make it easy to learn `R` as you go. We have set up a separate R Code for Loss Data Analytics site to explain more of the details of the code.

Like any book, we have a set of notations and conventions. It will probably save you time if you regularly visit our Appendix Chapter **??** to get used to ours.

Freely available, interactive textbooks represent a new venture in actuarial education and we need your input. Although a lot of effort has gone into the development, we expect hiccoughs. Please let your instructor know about opportunities for improvement, write us through our project site, or contact chapter contributors directly with suggested improvements.

Chapter 1

Loss Data and Insurance Activities

Chapter Preview. This book introduces readers to methods of analyzing insurance data. Section 1.1 begins with a discussion of why the use of data is important in the insurance industry. Section 1.2 gives a general overview of the purposes of analyzing insurance data which is reinforced in the Section 1.3 case study. Naturally, there is a huge gap between the broad goals summarized in the overview and a case study application; this gap is covered through the methods and techniques of data analysis covered in the rest of the text.

1.1 Data Driven Insurance Activities

In this section, you learn how to:

- Summarize the importance of insurance to consumers and the economy
- Describe the role that data plays in managing insurance activities
- Identify data generating events associated with the timeline of a typical insurance contract

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1.1.1 Nature and Relevance of Insurance

This book introduces the process of using data to make decisions in an insurance context. It does not assume that readers are familiar with insurance but introduces insurance concepts as needed. If you are new to insurance, then it is probably easiest to think about an insurance policy that covers the contents of an apartment or house that you are renting (known as renters insurance) or the contents and property of a building that is owned by you or a friend (known as homeowners insurance). Another common example is automobile insurance. In the event of an accident, this policy may cover damage to your vehicle, damage to other vehicles in the accident, as well as medical expenses of those injured in the accident.

One way to think about the nature of insurance is who buys it. Renters, homeowners, and auto insurance are examples of personal insurance in that these are policies issued to people. Businesses also buy insurance, such as coverage on their properties, and this is known as commercial insurance. The seller, an insurance company, is also known as an insurer. Even insurance companies need insurance; this is known as reinsurance.

Another way to think about the nature of insurance is the type of risk being covered. In the U.S., policies such as renters and homeowners are known as property insurance whereas a policy such as auto that covers medical damages to people is known as casualty insurance. In the rest of the world, these are both known as non-life or general insurance, to distinguish them from life insurance.

Both life and non-life insurances are important components of the world economy. The The Organization for Economic Cooperation and Development (OECD) estimates that direct insurance premiums in the OECD (Organization for Economic Cooperation and Development) countries for 2020 was 2,520,220 for life and 2,704,799 for non-life; these figures are in *millions of U.S. dollars*. The total represents 9.447% of the OECD gross domestic product (GDP). As examples, premiums accounted for 30.9% of GDP in Luxembourg and 17.0% of GDP in Chinese Taipei (the two highest in the study) and represented 12.5% of GDP in the United States. Both life and non-life insurances represent important economic activities.

Insurance affects the financial livelihoods of many and, by almost any measure, insurance is a major economic activity. As noted earlier, on a global level insurance premiums comprised nearly 9.5% of GDP in 2020. On a personal level, almost everyone owning a home has insurance to protect themselves in the event of a fire, hailstorm, or some other calamitous event. Almost every country requires insurance for those driving a car. In sum, insurance plays an important role in the economies of nations and the lives of individuals.

1.1.2 Why Data Driven?

Insurance is a data-driven industry. Like all major corporations and organizations, insurers use data when trying to decide how much to pay employees, how many employees to retain, how to market their services and products, how to forecast financial trends, and so on. These represent general areas of activities that are not specific to the insurance industry. Although each industry has its own data nuances and needs, the collection, analysis and use of data is an activity shared by all, from the internet giants to a small business, by public and governmental organizations, and is not specific to the insurance industry. You will find that the data collection and analysis methods and tools introduced in this text are relevant for all.

In any data-driven industry, deriving and extracting information from data is critical. Making data-driven business decisions has been described as business analytics, business intelligence, and data science. These terms, among others, are sometimes used interchangeably and sometimes refer to distinct applications. *Business intelligence* may focus on processes of collecting data, often through databases and data warehouses, whereas *business analytics* utilizes tools and methods for statistical analyses of data. In contrast to these two terms that emphasize business applications, the term *data science* can encompass broader data related applications in many scientific domains. For our purposes, we use the term analytics to refer to the process of using data to make decisions. This process involves gathering data, understanding concepts and models of uncertainty, making general inferences, and communicating results. Chapter **??** describes data analytics in further detail.

When introducing methods in this text, we focus on **loss data** that arise from, or are related to, obligations in insurance contracts. This could be the amount of damage to one's apartment under a renter's insurance agreement, the amount needed to compensate someone that you hurt in a driving accident, and the like. We call such payments an insurance claim. With this focus, we are able to introduce and directly use generally applicable statistical tools and techniques.

1.1.3 Insurance Processes

Yet another way to think about the nature of insurance is by the duration of an insurance contract, known as the term. This text will focus on short-term insurance contracts. By short-term, we mean contracts where the insurance coverage is typically provided for a year or six months. Most non-life commercial and personal contracts are for a year so that is our default duration. An important exception is U.S. auto policies that are often six months in length.

In contrast, we typically think of life insurance as a long-term contract where the default is to have a multi-year contract. For example, if a person 25 years old purchases a whole life policy that pays upon death of the insured and that person does not die until age 100, then the contract is in force for 75 years.

There are other important differences between life and non-life products. In life insurance, the benefit amount is often stipulated in the contract provisions. In contrast, most non-life contracts provide for compensation of insured losses which are unknown before the accident. (There are usually limits placed on the compensation amounts.) In a life insurance contract that stretches over many years, the time value of money plays a prominent role. In a non-life contract, the random amount of compensation takes priority.

In both life and non-life insurances, the frequency of claims is very important. For many life insurance contracts, the insured event (such as death) happens only once. In contrast, for non-life insurances such as automobile, it is common for individuals (especially young male drivers) to get into more than one accident during a year. So, our models need to reflect this observation; we introduce different frequency models that you may also see when studying life insurance.

For short-term insurance, the framework of the probabilistic model is straightforward. We think of a one-period model (the period length, e.g., one year, will be specified in the situation).

- At the beginning of the period, the insured pays the insurer a known premium that is agreed upon by both parties to the contract.
- At the end of the period, the insurer reimburses the insured for a (possibly multivariate) random loss.

This framework will be developed as we proceed; but we first focus on integrating this framework with concerns about how the data may arise. From an insurer's viewpoint, contracts may be only for a year but they tend to be renewed. Moreover, payments arising from claims during the year may extend well beyond a single year. One way to describe the data arising from operations of an insurance company is to use a timeline granular approach. A **process** approach provides an overall view of the events occurring during the life of an insurance contract, and their nature – random or planned, loss events (claims) and contract changes events, and so forth. In this micro oriented view, we can think about what happens to a contract at various stages of its existence.

Figure 1.1 traces a timeline of a typical insurance contract. Throughout the life of the contract, the company regularly processes events such as premium collection and valuation, described in Section 1.2; these are marked with an **x** on the timeline. Non-regular and unanticipated events also occur. To illustrate, t_2 and t_4 mark the event of an insurance claim (some contracts, such as life insurance, can have only a single claim). Times t_3 and t_5 mark events when a policyholder wishes to alter certain contract features, such as the choice of a deductible or the amount of coverage. From a company perspective, one can even think about the contract initiation (arrival, time t_1) and contract termination (departure, time t_6) as uncertain events. (Alternatively, for some purposes, you may condition on these events and treat them as certain.)

1.2 Insurance Company Operations

In this section, you learn how to:

- Describe five major operational areas of insurance companies.
- Identify the role of data and analytics opportunities within each operational area.

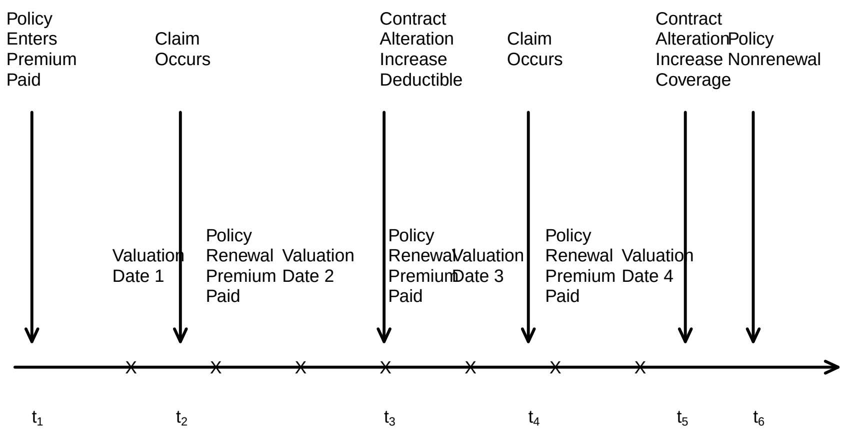


Figure 1.1: **Timeline of a Typical Insurance Policy.** Arrows mark the occurrences of random events. Each x marks the time of scheduled events that are typically non-random.

Armed with insurance data, the end goal is to use data to make decisions. We will learn more about methods of analyzing and extrapolating data in future chapters. To begin, let us think about why we want to do the analysis. We take the insurance company's viewpoint (not the insured person) and introduce ways of bringing money in, paying it out, managing costs, and making sure that we have enough money to meet obligations. The emphasis is on insurance-specific operations rather than on general business activities such as advertising, marketing, and human resources management.

Specifically, in many insurance companies, it is customary to aggregate detailed insurance processes into larger operational units; many companies use these functional areas to segregate employee activities and areas of responsibilities. Actuaries, other financial analysts, and insurance regulators work within these units and use data for the following activities:

1. **Initiating Insurance**. At this stage, the company makes a decision as to whether or not to take on a risk (the underwriting stage) and assign an appropriate premium (or rate). Insurance analytics has its actuarial roots in *ratemaking*, where analysts seek to determine the right price for the right risk.
2. **Renewing Insurance**. Many contracts, particularly in general insurance, have relatively short durations such as 6 months or a year. Although there is an implicit expectation that such contracts will be renewed, the insurer has the opportunity to decline coverage and to adjust the premium. Analytics is also used at this policy renewal stage where the goal is to retain profitable customers.
3. **Claims Management**. Analytics has long been used in (1) detecting and preventing claims fraud, (2) managing claim costs, including identifying the appropriate support for claims handling expenses, as well as (3) understanding excess layers for reinsurance and retention.
4. **Loss Reserving**. Analytic tools are used to provide management with an appropriate estimate of future obligations and to quantify the uncertainty of those estimates.
5. **Solvency and Capital Allocation**. Deciding on the requisite amount of capital and on ways of allocating capital among alternative investments are also important analytics activities. Companies must understand how much capital is needed so that they have sufficient flow of cash available to meet their obligations at the times they are expected to materialize (solvency). This is an important question that concerns not only company managers but also customers, company shareholders, regulatory authorities, as well as the public at large. Related to issues of how much capital is the question of how to allocate capital to differing financial projects, typically to maximize an investor's return. Although this question can arise at several levels, insurance companies are typically concerned with how to allocate capital to different lines of business within a firm and to different subsidiaries of a parent firm.

Although data represent a critical component of solvency and capital allocation, other components including the local and global economic framework, the financial investments environment, and quite specific requirements according to the regulatory environment of the day, are also important. Because of the background needed to address these components, we do not address solvency, capital allocation, and regulation issues in this text.

Nonetheless, for all operating functions, we emphasize that analytics in the insurance industry is not an exercise that a small group of analysts can do by themselves. It requires an insurer to make significant investments in their information technology, marketing, underwriting, and actuarial functions. As these areas represent the primary end goals of the analysis of data, additional background on each operational unit is provided in the following subsections.

1.2.1 Initiating Insurance

Setting the price of an insurance product can be a perplexing problem. This is in contrast to other industries such as manufacturing where the cost of a product is (relatively) known and provides a benchmark for assessing a market demand price. Similarly, in other areas of financial services, market prices are available and provide the basis for a market-consistent pricing structure of products. However, for many lines of insurance, the cost of a product is uncertain and market prices are unavailable. Expectations of the random cost is a reasonable place to start for a price. (If you have studied finance, then you will recall that an expectation is the optimal price for a risk-neutral insurer.) It has been traditional in insurance pricing to begin with the expected cost. Insurers then add margins to this, to account for the product's riskiness, expenses incurred in servicing the product, and an allowance for profit/surplus of the company.

Use of expected costs as a foundation for pricing is prevalent in some lines of the insurance business. These include automobile and homeowners insurance. For these lines, analytics has served to sharpen the market by making the calculation of the product's expected cost more precise. The increasing availability of the internet to consumers has also promoted transparency in pricing; in today's marketplace, consumers have ready access to competing quotes from a host of insurers. Insurers seek to increase their market share by refining their risk classification systems, thus achieving a better approximation of the products' prices and enabling cream-skimming underwriting strategies ("cream-skimming" is a phrase used when the insurer underwrites only the best risks). Surveys (e.g., Earnix (2013)) indicate that pricing is the most common use of analytics among insurers.

Underwriting, the process of classifying risks into homogeneous categories and assigning policyholders to these categories, lies at the core of ratemaking. Policyholders within a class (category) have similar risk profiles and so are charged the same insurance price. This is the concept of an actuarially fair premium; it is fair to charge different rates to policyholders only if they can be separated by identifiable risk factors. An early article, *Two Studies in Automobile Insurance Ratemaking* (Bailey and LeRoy, 1960), provided a catalyst to the acceptance of analytic methods in the insurance industry. This paper addresses the problem of classification ratemaking. It describes an example of automobile insurance that has five use classes cross-classified with four merit rating classes. At that time, the contribution to premiums for use and merit rating classes were determined independently of each other. Thinking about the interacting effects of different classification variables is a more difficult problem.

When the risk is initially obtained, the insurer's obligations can be managed by imposing contract parameters that modify contract payouts. Chapter **??** describes common modifications including coinsurance, deductibles and policy upper limits.

1.2.2 Renewing Insurance

Insurance is a type of financial service and, like many service contracts, insurance coverage is often agreed upon for a limited time period at which time coverage commitments are complete. Particularly for general insurance, the need for coverage continues and so efforts are made to issue a new contract providing similar coverage when the existing contract comes to the end of its term. This is called *policy renewal*. Renewal issues can also arise in life insurance, e.g., term (temporary) life insurance. At the same time other contracts, such as life annuities, terminate upon the insured's death and so issues of renewability are irrelevant.

In the absence of legal restrictions, at renewal the insurer has the opportunity to:

- accept or decline to underwrite the risk; and
- determine a new premium, possibly in conjunction with a new classification of the risk.

Risk classification and rating at renewal is based on two types of information. First, at the initial stage, the insurer has available many rating variables upon which decisions can be made. Many variables are not likely to change, e.g., sex, whereas others are likely to change, e.g., age, and still others may or may not change, e.g., credit score. Second, unlike the initial stage, at renewal the insurer has available a history of policyholder's loss experience, and this history can provide insights into the policyholder that are not available from rating variables. Modifying premiums with claims history is known as *experience rating*, also sometimes referred to as *merit rating*.

Experience rating methods are either applied retrospectively or prospectively. With retrospective methods, a refund of a portion of the premium is provided to the policyholder in the event of favorable (to the insurer) experience. Retrospective premiums are common in life insurance arrangements (where policyholders earn dividends in the U.S., bonuses in the U.K., and profit sharing in Israeli term life coverage). In general insurance, prospective methods are more common, where favorable insured experience is rewarded through a lower renewal premium.

Claims history can provide information about a policyholder's risk appetite. For example, in personal lines it is common to use a variable to indicate whether or not a claim has occurred in the last three years. As another example, in a commercial line such as worker's compensation, one may look to a policyholder's average claim frequency or severity over the last three years. Claims history can reveal information that is otherwise hidden (to the insurer) about the policyholder.

1.2.3 Claims and Product Management

In some of types of insurance, the process of paying claims for insured events is relatively straightforward. For example, in life insurance, a simple death certificate is all that is needed to pay the benefit amount as provided in the contract. However, in non-life areas such as property and casualty insurance, the process can be much more complex. Think about a relatively simple insured event such as an automobile accident. Here, it is often required to determine which party is at fault and then one needs to assess damage to all of the vehicles and people involved in the incident, both insured and non-insured. Further, the expenses incurred in assessing the damages must be assessed, and so forth. The process of determining coverage, legal liability, and settling claims is known as claims adjustment.

Insurance managers sometimes use the phrase claims leakage to mean dollars lost through claims management inefficiencies. There are many ways in which analytics can help manage the claims process, c.f., Gorman and Swenson (2013). Historically, the most important has been fraud detection. The claim adjusting process involves reducing information asymmetry (the claimant knows what happened; the company knows some of what happened). Mitigating fraud is an important part of the claims management process.

Fraud detection is only one aspect of managing claims. More broadly, one can think about claims management as consisting of the following components:

- **Claims triaging**. Just as in the medical world, early identification and appropriate handling of high cost claims (patients, in the medical world), can lead to dramatic savings. For example, in workers compensation, insurers look to achieve early identification of those claims that run the risk of high medical costs and a long payout period. Early intervention into these cases could give insurers more control over the handling of the claim, the medical treatment, and the overall costs with an earlier return-to-work.
- **Claims processing**. The goal is to use analytics to identify routine situations that are anticipated to have small payouts. More complex situations

may require more experienced adjusters and legal assistance to appropriately handle claims with high potential payouts.

- **Adjustment decisions**. Once a complex claim has been identified and assigned to an adjuster, analytic driven routines can be established to aid subsequent decision-making processes. Such processes can also be helpful for adjusters in developing case reserves, an estimate of the insurer's future liability. This is an important input to the insurer's loss reserves, described in Section 1.2.4.

In addition to the insured's reimbursement for losses, the insurer also needs to be concerned with another source of revenue outflow, expenses. Loss adjustment expenses are part of an insurer's cost of managing claims. Analytics can be used to reduce expenses directly related to claims handling (allocated) as well as general staff time for overseeing the claims processes (unallocated). The insurance industry has high operating costs relative to other portions of the financial services sectors.

In addition to claims payments, there are many other ways in which insurers use data to manage their products. We have already discussed the need for analytics in underwriting, that is, risk classification at the initial acquisition and renewal stages. Insurers are also interested in which policyholders elect to renew their contracts and, as with other products, monitor customer loyalty.

Analytics can also be used to manage the portfolio, or collection, of risks that an insurer has acquired. As described in Chapter **??**, after the contract has been agreed upon with an insured, the insurer may still modify its net obligation by entering into a reinsurance agreement. This type of agreement is with a reinsurer, an insurer of an insurer. It is common for insurance companies to purchase insurance on its portfolio of risks to gain protection from unusual events, just as people and other companies do.

1.2.4 Loss Reserving

An important feature that distinguishes insurance from other sectors of the economy is the timing of the exchange of considerations. In manufacturing, payments for goods are typically made at the time of a transaction. In contrast, for insurance, money received from a customer occurs in advance of benefits or services; these are rendered at a later date if the insured event occurs. This leads to the need to hold a reservoir of wealth to meet future obligations in respect to obligations made, and to gain the trust of the insureds that the company will be able to fulfill its commitments. The size of this reservoir of wealth, and the importance of ensuring its adequacy, is a major concern for the insurance industry.

Setting aside money for unpaid claims is known as loss reserving; in some jurisdictions, reserves are also known as *technical provisions*. We saw in Figure 1.1 several times at which a company summarizes its financial position; these times are known as valuation dates. Claims that arise prior to valuation dates have either been paid, are in the process of being paid, or are about to be paid; claims in the future of these valuation dates are unknown. A company must estimate these outstanding liabilities when determining its financial strength. Accurately determining loss reserves is important to insurers for many reasons.

1. Loss reserves represent an anticipated claim that the insurer owes its customers. Under-reserving may result in a failure to meet claim liabilities. Conversely, an insurer with excessive reserves may present a conservative estimate of surplus and thus portray a weaker financial position than it truly has.
2. Reserves provide an estimate for the unpaid cost of insurance that can be used for pricing contracts.
3. Loss reserving is required by laws and regulations. The public has a strong interest in the financial strength and solvency of insurers.
4. In addition to regulators, other stakeholders such as insurance company management, investors, and customers make decisions that depend on company loss reserves. Whereas regulators and customers appreciate conservative estimates of unpaid claims, managers and investors seek more unbiased estimates to represent the true financial health of the company.

Loss reserving is a topic where there are substantive differences between life and general (also known as property and casualty, or non-life) insurance. In life insurance, the severity (amount of loss) is often not a source of uncertainty as payouts are specified in the contract. The frequency, driven by mortality of the insured, is a concern. However, because of the lengthy time for settlement of life insurance contracts, the time value of money uncertainty as measured from issue to date of payment can dominate frequency concerns. For example, for an insured who purchases a life contract at age 20, it would not be unusual for the contract to still be open in 60 years time, when the insured celebrates his or her 80th birthday. See, for example, Bowers et al. (1986) or Dickson et al. (2013) for introductions to reserving for life insurance. In contrast, for most lines of non-life business, severity is a major source of uncertainty and contract durations tend to be shorter.

1.3 Case Study: Wisconsin Property Fund

In this section, we use the Wisconsin Property Fund as a case study. You learn how to:

- Describe how data generating events can produce data of interest to insurance analysts.
- Produce relevant summary statistics for each variable.
- Describe how these summary statistics can be used in each of the major operational areas of an insurance company.

Let us illustrate the kind of data under consideration and the goals that we wish to achieve by examining the Local Government Property Insurance Fund (LGPIF), an insurance pool administered by the Wisconsin Office of the Insurance Commissioner. The LGPIF was established to provide property insurance for local government entities that include counties, cities, towns, villages, school districts, and library boards. The fund insures local government property such as government buildings, schools, libraries, and motor vehicles. It covers all property losses except those resulting from flood, earthquake, wear and tear, extremes in temperature, mold, war, nuclear reactions, and embezzlement or theft by an employee.

The fund covers over a thousand local government entities who pay approximately 25 million dollars in premiums each year and receive insurance coverage of about 75 billion. State government buildings are not covered; the LGPIF is for local government entities that have separate budgetary responsibilities and who need insurance to moderate the budget effects of uncertain insurable events. Coverage for local government property has been made available by the State of Wisconsin since 1911, thus providing a wealth of historical data.

In this illustration, we restrict consideration to claims from coverage of building and contents; we do not consider claims from motor vehicles and specialized equipment owned by local entities (such as snow plowing machines). We also consider only claims that are closed, with obligations fully met.

1.3.1 Fund Claims Variables: Frequency and Severity

At a fundamental level, insurance companies accept premiums in exchange for promises to compensate a policyholder upon the occurrence of an insured event. Indemnification is the compensation provided by the insurer for incurred hurt, loss, or damage that is covered by the policy. This compensation is also known as a *claim*. The extent of the payout, known as the *severity*, is a key financial expenditure for an insurer.

In terms of money outgo, an insurer is indifferent to having ten claims of 100 when compared to one claim of 1,000. Nonetheless, it is common for insurers to study how often claims arise, known as the *frequency* of claims. The frequency is important for expenses, but it also influences contractual parameters (such as deductibles and policy limits that are described later) that are written on a per occurrence basis. Frequency is routinely monitored by insurance regulators and can be a key driver in the overall indemnification obligation of the insurer. We shall consider the frequency and severity as the two main claim variables that we wish to understand, model, and manage.

To illustrate, in 2010 there were 1,110 policyholders in the property fund who experienced a total of 1,377 claims. Table 1.1 shows the distribution. Almost two-thirds (0.637) of the policyholders did not have any claims and an additional

18.8% had only one claim. The remaining 17.5% (=1 - 0.637 - 0.188) had more than one claim; the policyholder with the highest number recorded 239 claims. The average number of claims for this sample was 1.24 (=1377/1110).

Table 1.1. **2010 Claims Frequency Distribution**

Type											
Number	0	1	2	3	4	5	6	7	8	9 or more	Sum
Policies	707	209	86	40	18	12	9	4	6	19	1,110
Claims	0	209	172	120	72	60	54	28	48	617	1,377
Proportion	0.637	0.188	0.077	0.036	0.016	0.011	0.008	0.004	0.005	0.017	1.000

For the severity distribution, a common approach is to examine the distribution of the sample of 1,377 claims. However, another common approach is to examine the distribution of the average claims of those policyholders with claims. In our 2010 sample, there were 403 (=1110-707) such policyholders. For 209 of these policyholders with one claim, the average claim equals the only claim they experienced. For the policyholder with highest frequency, the average claim is an average over 239 separately reported claim events. This average is also known as the pure premium or *loss cost*.

Table 1.2 summarizes the sample distribution of average severities from the 403 policyholders who made a claim; it shows that the average claim amount was 56,330 (all amounts are in U.S. Dollars). However, the average gives only a limited look at the distribution. More information can be gleaned from the summary statistics which show a very large claim in the amount of 12,920,000. Figure 1.2 provides further information about the distribution of sample claims, showing a distribution that is dominated by this single large claim so that the histogram is not very helpful. Even when removing the large claim, you will find a distribution that is skewed to the right. A generally accepted technique is to work with claims in logarithmic units especially for graphical purposes; the corresponding figure in the right-hand panel is much easier to interpret.

Table 1.2. **2010 Average Severity Distribution**

Minimum	First Quartile	Median	Mean	Third Quartile	Maximum
167	2,226	4,951	56,330	11,900	12,920,000

1.3.2 Fund Rating Variables

Developing models to represent and manage the two outcome variables, frequency and severity, is the focus of the early chapters of this text. However, when actuaries and other financial analysts use those models, they do so in the

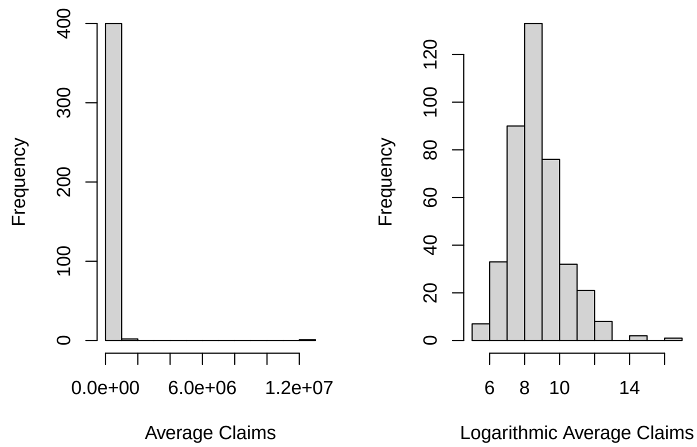


Figure 1.2: **Distribution of Positive Average Severities**

context of external variables. In general statistical terminology, one might call these explanatory or predictor variables; there are many other names in statistics, economics, psychology, and other disciplines. Because of our insurance focus, we call them rating variables as they are useful in setting insurance rates and premiums.

We earlier considered observations from a sample of 1,110 policyholders which may seem like a lot. However, as we will see in our forthcoming applications, because of the preponderance of zeros and the skewed nature of claims, actuaries typically yearn for more data. One common approach that we adopt here is to examine outcomes from multiple years, thus increasing the sample size. We will discuss the strengths and limitations of this strategy later but, at this juncture, we just wish to show the reader how it works.

Specifically, Table 1.3 shows that we now consider policies over five years of data, 2006, ..., 2010, inclusive. The data begins in 2006 because there was a shift in claim coding in 2005 so that comparisons with earlier years are not helpful. To mitigate the effect of open claims, we consider policy years prior to 2011. An open claim means that not all of the obligations for the claim are known at the time of the analysis; for some claims, such an injury to a person in an auto accident or in the workplace, it can take years before costs are fully known.

Table 1.3. **Claims Summary by Policyholder**

Year	Average Frequency	Average Severity	Average Coverage	Number of Policyholders
2006	0.951	9,695	32,498,186	1,154
2007	1.167	6,544	35,275,949	1,138
2008	0.974	5,311	37,267,485	1,125
2009	1.219	4,572	40,355,382	1,112
2010	1.241	20,452	41,242,070	1,110

Table 1.3 shows that the average claim varies over time, especially with the high 2010 value (that we saw was due to a single large claim)[1]. The total number of policyholders is steadily declining and, conversely, the coverage is steadily increasing. The coverage variable is the amount of coverage of the property and contents. Roughly, you can think of it as the maximum possible payout of the insurer. For our immediate purposes, the coverage is our first rating variable. Other things being equal, we would expect that policyholders with larger coverage have larger claims. We will make this vague idea much more precise as we proceed, and also justify this expectation with data.

For a different look at the 2006-2010 data, Table 1.4 summarizes the distribution of our two outcomes, frequency and claims amount. In each case, the average exceeds the median, suggesting that the two distributions are right-skewed. In addition, the table summarizes our continuous rating variables, coverage and deductible amount. The table also suggests that these variables also have right-skewed distributions.

Table 1.4. **Summary of Claim Frequency and Severity, Deductibles, and Coverages**

	Minimum	Median	Average	Maximum
Claim Frequency	0	0	1.109	263
Claim Severity	0	0	9,292	12,922,218
Deductible	500	1,000	3,365	100,000
Coverage (000's)	8.937	11,354	37,281	2,444,797

Table 1.5 describes the rating variables considered in this chapter. Hopefully, these are variables that you think might naturally be related to claims outcomes. You can learn more about them in Frees et al. (2016). To handle the skewness, we henceforth focus on logarithmic transformations of coverage and deductibles.

Table 1.5. **Description of Rating Variables**

[1]Note that the average severity in Table 1.3 differs from that reported in Table 1.2. This is because the former includes policyholders with zero claims where as the latter does not. This is an important distinction that we will address in later portions of the text.

Variable	*Description*
EntityType	Categorical variable that is one of six types: (Village, City, County, Misc, School, or Town)
LnCoverage	Total building and content coverage, in logarithmic millions of dollars
LnDeduct	Deductible, in logarithmic dollars
AlarmCredit	Categorical variable that is one of four types: (0, 5, 10, or 15) for automatic smoke alarms in main rooms
NoClaimCredit	Binary variable to indicate no claims in the past two years
Fire5	Binary variable to indicate the fire class is below 5 (The range of fire class is 0 to 10)

To get a sense of the relationship between the non-continuous rating variables and claims, Table 1.6 relates the claims outcomes to these categorical variables. Table 1.6 suggests substantial variation in the claim frequency and average severity of the claims by entity type. It also demonstrates higher frequency and severity for the `Fire5` variable and the reverse for the `NoClaimCredit` variable. The relationship for the `Fire5` variable is counter-intuitive in that one would expect lower claim amounts for those policyholders in areas with better public protection (when the protection code is five or less). Naturally, there are other variables that influence this relationship. We will see that these background variables are accounted for in the subsequent multivariate regression analysis, which yields an intuitive, appealing (negative) sign for the `Fire5` variable.

Table 1.6. **Claims Summary by Entity Type, Fire Class, and No Claim Credit**

Variable	Number of Policies	Claim Frequency	Average Severity
EntityType			
Village	1,341	0.452	10,645
City	793	1.941	16,924
County	328	4.899	15,453
Misc	609	0.186	43,036
School	1,597	1.434	64,346
Town	971	0.103	19,831
Fire			
Fire5=0	2,508	0.502	13,935
Fire5=1	3,131	1.596	41,421
No Claims Credit			
NoClaimCredit=0	3,786	1.501	31,365
NoClaimCredit=1	1,853	0.310	30,499
Total	5,639	1.109	31,206

Table 1.7 shows the claims experience by alarm credit. It underscores the difficulty of examining variables individually. For example, when looking at the

experience for all entities, we see that policyholders with no alarm credit have on average lower frequency and severity than policyholders with the highest (15%, with 24/7 monitoring by a fire station or security company) alarm credit. In particular, when we look at the entity type School, the frequency is 0.422 and the severity 25,523 for no alarm credit, whereas for the highest alarm level it is 2.008 and 85,140, respectively. This may simply imply that entities with more claims are the ones that are likely to have an alarm system. Summary tables do not examine multivariate effects; for example, Table 1.6 ignores the effect of size (as we measure through coverage amounts) that affect claims.

Table 1.7. **Claims Summary by Entity Type and Alarm Credit (AC) Category**

Entity Type	AC0 Claim Frequency	AC0 Avg. Severity	AC0 Num. Policies	AC5 Claim Frequency	AC5 Avg. Severity	AC5 Num. Policies
Village	0.326	11,078	829	0.278	8,086	54
City	0.893	7,576	244	2.077	4,150	13
County	2.140	16,013	50	-	-	1
Misc	0.117	15,122	386	0.278	13,064	18
School	0.422	25,523	294	0.410	14,575	122
Town	0.083	25,257	808	0.194	3,937	31
Total	0.318	15,118	2,611	0.431	10,762	239

Entity Type	AC10 Claim Frequency	AC10 Avg. Severity	AC10 Num. Policies	AC15 Claim Frequency	AC15 Avg. Severity	AC15 Num. Policies
Village	0.500	8,792	50	0.725	10,544	408
City	1.258	8,625	31	2.485	20,470	505
County	2.125	11,688	8	5.513	15,476	269
Misc	0.077	3,923	26	0.341	87,021	179
School	0.488	11,597	168	2.008	85,140	1,013
Town	0.091	2,338	44	0.261	9,490	88
Total	0.517	10,194	327	2.093	41,458	2,462

We will learn more about modeling count data in the Chapter **??** and about severity data in Chapters **??** and **??**.

1.3.3 Fund Operations

We have now seen distributions of the Fund's two outcome variables: a count variable for the number of claims, and a continuous variable for the claims amount. We have also introduced a continuous rating variable (coverage); a discrete quantitative variable (logarithmic deductibles); two binary rating variables (no claims credit and fire class); and two categorical rating variables (entity type and alarm credit). Subsequent chapters will explain how to analyze and model the distribution of these variables and their relationships. Before getting into these technical details, let us first think about where we want to go. General insurance company functional areas are described in Section 1.2; we now consider how these areas might apply in the context of the property fund.

Initiating Insurance

Because this is a government sponsored fund, we do not have to worry about selecting good or avoiding poor risks; the fund is not allowed to deny a coverage application from a qualified local government entity. If we do not have to underwrite, what about how much to charge?

We might look at the most recent experience in 2010, where the total fund claims were approximately 28.16 million USD ($= 1377$ claims $\times$ 20452 average severity). Dividing that among 1,110 policyholders, that suggests a rate of 24,370 ($\approx$ 28,160,000/1110). However, 2010 was a bad year; using the same method, our premium would be much lower based on 2009 data. This swing in premiums would defeat the primary purpose of the fund, to allow for a steady charge that local property managers could utilize in their budgets.

Having a single price for all policyholders is nice but hardly seems fair. For example, Table 1.6 suggests that schools have higher aggregate claims than other entities and so should pay more. However, simply doing the calculation on an entity by entity basis is not right either. For example, we saw in Table 1.7 that had we used this strategy, entities with a 15% alarm credit (for good behavior, having top alarm systems) would actually wind up paying more.

So, we have the data for thinking about the appropriate rates to charge but need to dig deeper into the analysis. We will explore this topic further in Chapter **??** on *premium calculation fundamentals*. Selecting appropriate risks is introduced in Chapter **??** on *risk classification*.

Renewing Insurance

Although property insurance is typically a one-year contract, Table 1.3 suggests that policyholders tend to renew; this is typical of general insurance. For renewing policyholders, in addition to their rating variables we have their claims history and this claims history can be a good predictor of future claims. For example, Table 1.6 shows that policyholders without a claim in the last two years had much lower claim frequencies than those with at least one accident (0.310 compared to 1.501); a lower predicted frequency typically results in a lower premium. This is why it is common for insurers to use variables such as `NoClaimCredit` in their rating. We will explore this topic further in Chapters **??** and **??** on *experience rating*.

Claims Management

Of course, the main story line of the 2010 experience was the large claim of over 12 million USD, nearly half the amount of claims for that year. Are there ways that this could have been prevented or mitigated? Are their ways for the fund to purchase protection against such large unusual events? Another unusual feature of the 2010 experience noted earlier was the very large frequency of claims (239) for one policyholder. Given that there were only 1,377 claims that year, this means that a single policyholder had 17.4 % of the claims. These extreme features of the data suggests opportunities for managing claims, the subject of Chapter **??**.

Loss Reserving

In our case study, we look only at the one year outcomes of closed claims (the opposite of open). However, like many lines of insurance, obligations from insured events to buildings such as fire, hail, and the like, are not known immediately and may develop over time. Other lines of business, including those where there are injuries to people, take much longer to develop. Chapter **??** introduces this concern and *loss reserving*, the discipline of determining how much the insurance company should retain to meet its obligations.

1.4 Exercises

These exercises ask you to work with data using statistical software, such as `R` code. If you would like some practice with `R` code, please visit the first chapter of a *Short Course on Loss Data Analytics.* As another method of learning, you can also get practice executing 'R' code at our Online Version R Code Site.

Exercise 1.1. Corporate Travel. Universities purchase corporate travel policies to cover employees and students traveling on official university business for a wide variety of accidents and incidents while away from the campus or primary workplace. This broad coverage includes medical care and evacuation, loss of personal property, extraction for political and weather related reasons, and more. These data represent experience from the Australian National University (ANU) and additional details can be found in ANU's corporate travel policy. You can also learn more about this line of business from ANU's insurer, Chubb Travel. The data provided are maintained by the insurer, Chubb, and were accessed on 29 July 2022. You can retrieve the data by going to Appendix Section 2.2.

a. Claim Frequency. The travel data history is long and stable. This coverage began on 1 November 2006. Table 1.9 shows the count of claims for years 2015-2019, inclusive. Produce a comparable table of claims frequency for the entire period. Comment on the unusual frequency surrounding the COVID pandemic.

b. Adjust for Zero Claims. From this data set, there are 2107 incurred claims. Of

Table 1.8: **2015-2019 Travel Claims Frequency**

2015	2016	2017	2018	2019
158	154	139	205	274

Table 1.9: **2015-2019 Travel Claims Frequency**

2015	2016	2017	2018	2019
158	154	139	205	274

these claims, there are 269 zeros and an additional 3 claims where the incurred claim is less than 10. We omit these claims in our analysis. Reproduce your part (a) analysis by omitting incurred claims less than 10.

c. Loss Distributions over Time. There are 1835 incurred losses in the dataset with all available years (yet omitting claims less than 10). Figure 1.3 shows that the distribution of incurred losses is stable over the period 2015-2019, inclusive. Produce a comparable figure for the entire period.

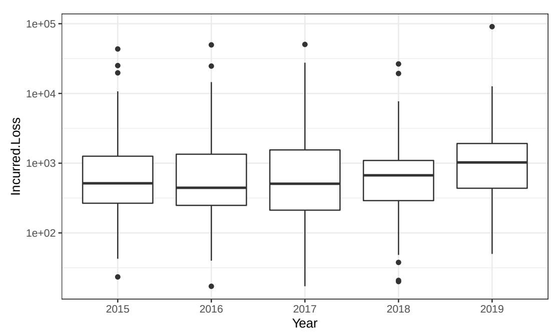


Figure 1.3: **Distribution of Travel Losses by Year**

d. Summary Statistics. In addition to graphs, it can be helpful to display several summary statistics. For the five year period 2015-2019, produce a set of summary statistics.

```
# a
TravelClaims <- read.csv("Data/ANUTravelClaims2022.csv", header = T)
tableTravel <- t(table(TravelClaims$UW.Year))
knitr::kable(tableTravel, align = "cccccccc", caption = "**Travel Claims Frequency**")
```

```
# b
TravelClaimsGT10 <- subset(TravelClaims, Incurred.Loss >= 10)
tableTravel1 <- t(table(TravelClaimsGT10$UW.Year))
```

Table 1.10: **Travel Claims Frequency**

2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	202
41	74	102	166	158	141	143	161	158	158	154	139	205	274	1	32

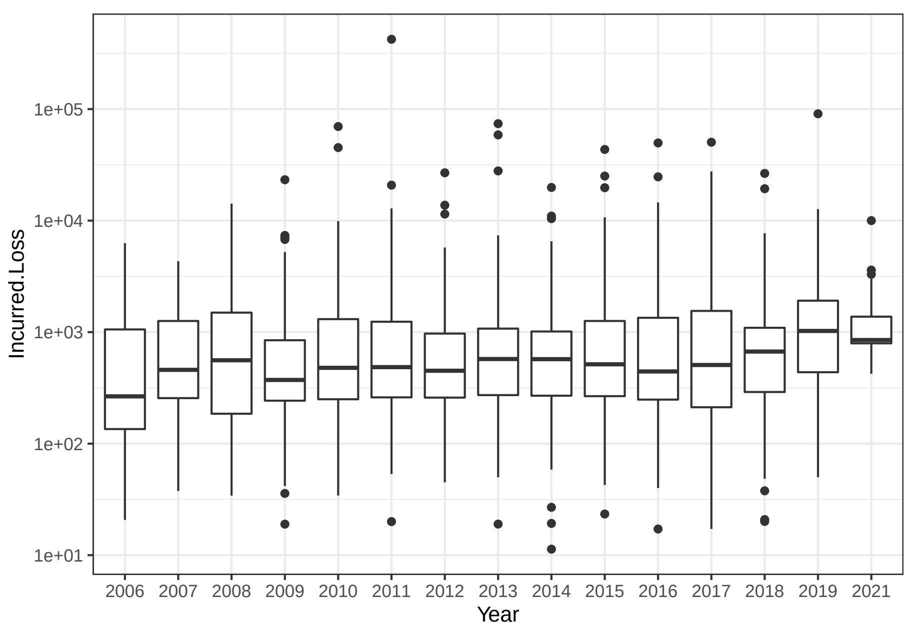
Table 1.11: **Travel Claims Frequency**

2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2021
31	58	86	154	153	136	135	140	132	142	132	129	170	207	30

```
knitr::kable(tableTravel1, align = "cccccccc", caption = "**Travel Claims Frequency**")
```

```
# c

ggplot(data = TravelClaimsGT10, aes(x = factor(UW.Year), y = Incurred.Loss)) + geom_boxplot() +
    theme_bw() + xlab("Year") + scale_y_continuous(trans = "log10")
```




```
# d

sumTravelClaims <- t(summary(TravelClaimsGT10Short$Incurred.Loss))
knitr::kable(sumTravelClaims, align = "cccccccc", caption = "**Travel Claims Summary Statistics**
```

Table 1.12: **Travel Claims Summary Statistics**

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
17.16	290.215	631.49	1701.953	1528.44	90727.64

Table 1.13: **2015-2019 Group Personal Accident Claims Frequency**

2015	2016	2017	2018	2019
4	7	16	11	9

Exercise 1.2. Group Personal Accident. Group personal accident insurance offers financial protection in case of injury or death resulting from an incident that occurs on the job. Group personal accident offers insurance coverage and liability insurance protection against accidental death or injury. The insurance covers students and ANU's voluntary workers; ANU workers are covered through another system known as "workers' compensation."

Several limits apply including 1,000,000 for the period of insurance, 600,000 for non-scheduled flights, and others. These limits were not reached in the data we consider. For this coverage, there is a "7 day excess" for weekly benefits but none for general benefits. The database documentation provided to us, and the data we provide, do not indicate whether the excess has been triggered; we have only paid claims. Because of the relatively small size of this class of insurance, we ignore the effects of deductibles for this line.

The data provided to us are maintained by the insurer, Chubb. These data began in underwriting year 2007 and were accessed on 29 July 2022. You can retrieve the data by going to Appendix Section 2.3.

a. Claim Frequency. From this data set, there are 148 incurred claims. Of these claims, there are 35 zeros and an additional 0 claims where the incurred claim is less than 10. We omit these claims in our analysis. Table 1.13 shows the count of claims for years 2015-2019, inclusive. Produce a comparable table of claims frequency for the entire period, omitting claims that are less than 10.

b. Skewness of Claims Severity Distribution. The left-hand panel of Figure 1.4 shows a histogram of incurred claims that reveals the right-skewed nature of this distribution. The right-hand panel shows the same claims but on the log (base 10) scale; this plot demonstrates that the log transform can symmetrize a distribution. These plots are for the 2015-2019 data. Replicate this work, using incurred claims for all available years (still omitting those less than 10).

c. Summary Statistics. Produce summary statistics for both claims and log claims using all available years (still omitting those less than 10). Comment on the relationship between the mean and the median for both claims and log claims, relating this to the symmetry of the distributions observed in part (b).

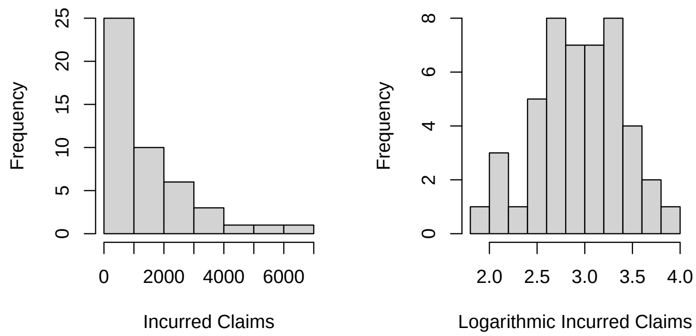


Figure 1.4: **Distribution of Incurred Claims 2015-2019**

d. Loss Distributions over Time. There are 112 incurred losses. Figure 1.5 indicates that the incurred losses are stable over the period 2015-2019, inclusive. Produce a comparable figure for the entire period and comment on the stability of the distribution.

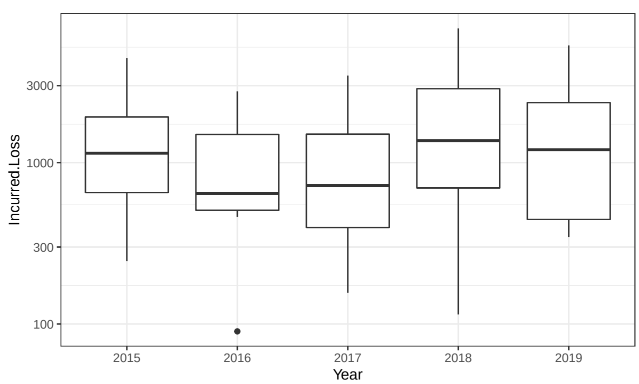


Figure 1.5: **Distribution of Group Personal Accident Losses by Year**

```
# a
GPAClaims <- read.csv("Data/ANUGroupPersonalAccidentClaims2022.csv", header = T)
GPAClaimsGT10 <- subset(GPAClaims, Incurred.Loss >= 10)
tableGPAFreq <- table(GPAClaimsGT10$UW.Year)
knitr::kable(t(tableGPAFreq), align = "cccccccc", caption = "**Group Personal Accident Claims Fre
```

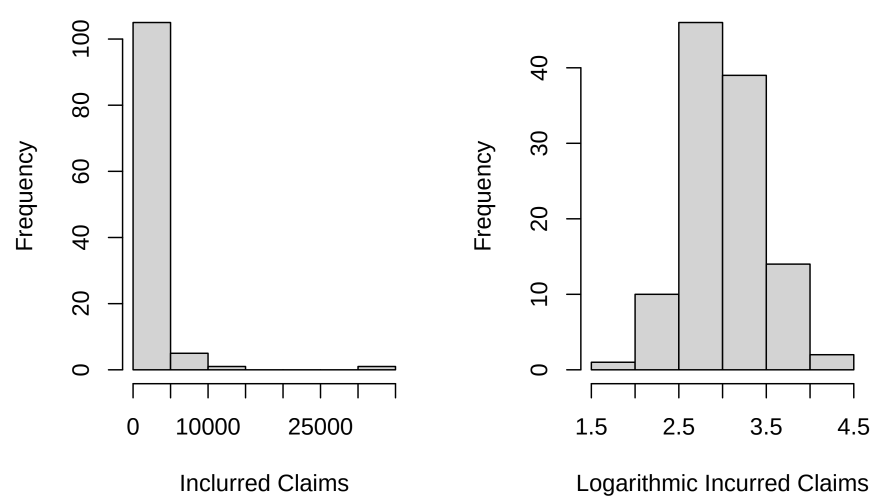
Table 1.14: **Group Personal Accident Claims Frequency**

2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
3	5	4	8	8	4	7	16	11	9	28	9

Table 1.15: **Group Personal Accident Incurred Losses**

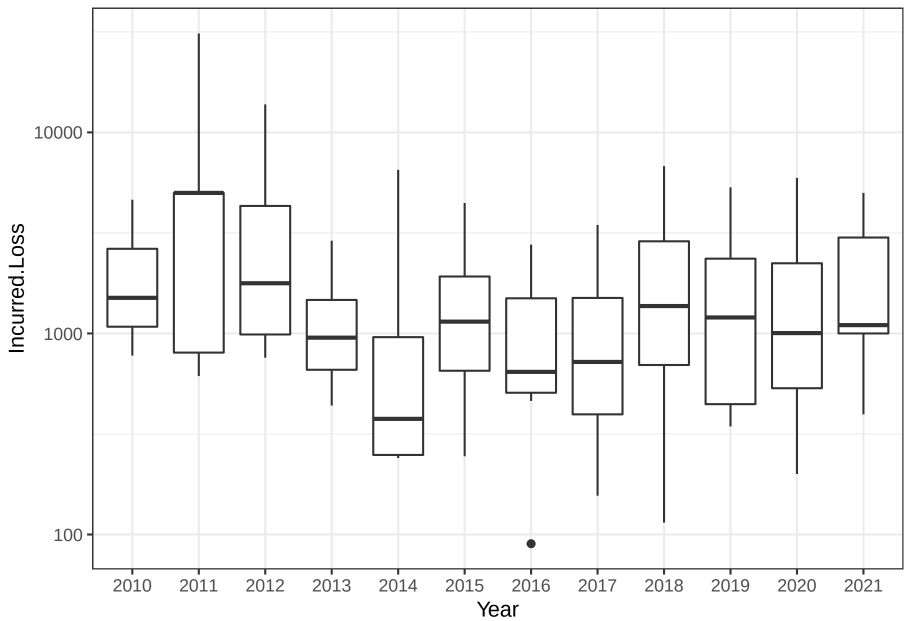
	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Claims	90.000	500.000	1000	2000.000	2000.000	30000.000
Log Claims	1.954	2.705	3	3.033	3.389	4.492

```
# b
par(mfrow = c(1, 2))
hist(GPAClaimsGT10$Incurred.Loss, main = "", xlab = "Inclurred Claims")
hist(log10(GPAClaimsGT10$Incurred.Loss), main = "", xlab = "Logarithmic Incurred Claims
```




```
# c
sumGPAClaimsGT10 <- t(summary(GPAClaimsGT10$Incurred.Loss, digits = 0))
LogsumGPAClaimsGT10 <- t(summary(log10(GPAClaimsGT10$Incurred.Loss), digits = 4))
tabSumStats <- rbind(sumGPAClaimsGT10, LogsumGPAClaimsGT10)
rownames(tabSumStats) <- c("Claims", "Log Claims")
knitr::kable(tabSumStats, align = "ccccccc", caption = "**Group Personal Accident Inc
```

```r
# d
ggplot(data = GPAClaimsGT10, aes(x = factor(UW.Year), y = Incurred.Loss)) + geom_boxplot() +
    theme_bw() + xlab("Year") + scale_y_continuous(trans = "log10")
```



Exercise 1.3. Motor Vehicle. This policy covers ANU's vehicles including cars, vans, utilities, and motorcycles. There are two parts to this coverage, one for comprehensive damage to the insured vehicles and a second for legal liability. The comprehensive coverage for loss or damage is essentially limited by the market value of the insured vehicle. For legal liability, there is a $50 Million upper limit for all claims arising from the one accident or series of accidents resulting from the one original cause. There is also another upper limit (that is lower than 50 million) when the vehicle is used for transportation of dangerous goods.

The data available contain the amount paid by the insurer (Vero Insurance Limited) which is the focus of our initial analysis. In addition, the data also contains a deductible (called an "excess" in the data file) that we explore in later parts.

The data provided to us are maintained by the insurer, Vero Insurance Limited. These data began in underwriting year 2012 and were accessed on 8 August 2022. You can retrieve the data by going to Appendix Section 2.4.

a. Adjust for Zeros. From this data set, check that:

Table 1.16: **Motor Vehicle Excess by Year**

UW.Year	Num 0	Num 0-1000	Num = 1000	Num >1000	Total
2011	1	1	7	0	9
2012	1	2	13	0	16
2013	4	1	22	0	27
2014	0	0	11	0	11
2015	1	1	14	0	16
2016	6	1	19	0	26
2017	16	0	4	1	21
2018	19	0	1	0	20
2019	99	0	6	0	105
2020	5	0	0	0	5
2021	10	0	0	0	10

- there are 318 incurred claims.
- Of these claims, there are 50 zeros and
- an additional 0 claims where the incurred claim is less than 10.

Remove these claims in your analysis, so that there are 268 incurred claims.

b. Claim Frequency. Produce a table that shows the count of claims for the entire period.

c. Loss Distributions over Time. Produce a figure that shows the distribution of motor vehicle paid amounts over time and comment on the stability of the distribution.

d. Year 2019. In your analysis from the prior steps, you may have noticed the unusual aspects of year 2019. In that year, ANU suffered extensive damage from a hailstorm that increased the frequency of claims as well as the severity. Produce a histogram of paid claims for that year.

e. Deductibles. For each event, or series of events arising from the one originating cause, ANU bears the amount of the excess in respect of each and every insured vehicle, unless stated otherwise. The standard deductible (or excess) in the dataset is 1000. However, a cursory examination of the dataset shows tremendous variation by vehicle and over time.Replicate Table 1.16 that shows, for each year, the number of claims with zero excess, positive excess less than 1000, an excess equal to 1000, and an excess greater than 1000.

(**Deductibles**. We recommend that motivated readers extend our analysis to account for this deductible in both the severity and frequency.)

```
# a
AutoClaims <- read.csv("Data/ANUMotorClaims2022.csv", header = T)
length(AutoClaims$Motor.Net.Incurred)  # Number of incurred claims
```

Table 1.17: **Motor Vehicle Claim Frequency**

2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
10	17	27	11	16	26	21	20	105	5	10

```
[1] 318
```

```
sum(AutoClaims$Motor.Net.Incurred == 0)  # Number of zeros and
```

```
[1] 50
```

```
sum((AutoClaims$Motor.Net.Incurred > 0) * (AutoClaims$Motor.Net.Incurred < 10))  # Number of incu
```

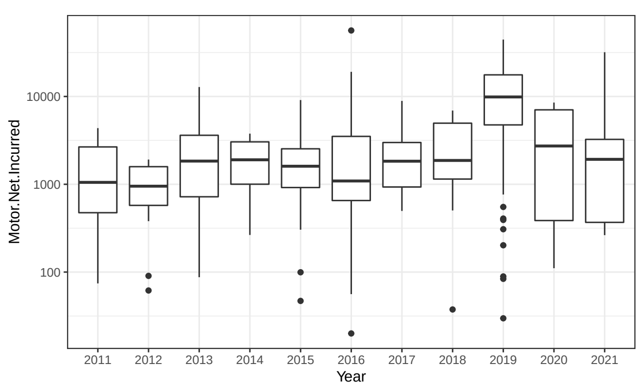
```
[1] 0
```

```
AutoClaimsGT10 <- subset(AutoClaims, Motor.Net.Incurred >= 10)
length(AutoClaimsGT10$Motor.Net.Incurred)  # length of the smaller dataset
```

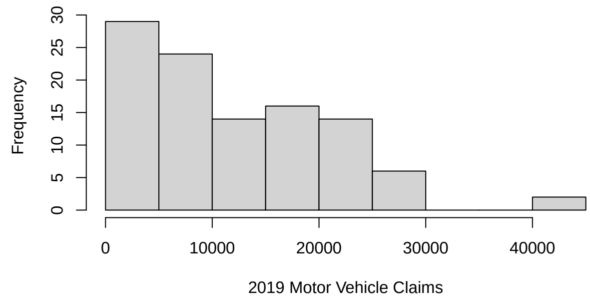
```
[1] 268
```

```
# b
UwYear <- as.Date(AutoClaimsGT10$Policy.Term.Start.Date, "%d/%m/%Y")
AutoClaimsGT10$UW.Year <- as.numeric(format(UwYear, format = "%Y"))
tableAutoClaims <- t(table(AutoClaimsGT10$UW.Year))
knitr::kable(tableAutoClaims, align = "cccccccc", caption = "**Motor Vehicle Claim Frequency**")
```

```
# c
ggplot(data = AutoClaimsGT10, aes(x = factor(UW.Year), y = Motor.Net.Incurred)) +
    geom_boxplot() + theme_bw() + xlab("Year") + scale_y_continuous(trans = "log10")
```



```
# d
AutoClaims2019 <- subset(AutoClaimsGT10, UW.Year == 2019)
hist(AutoClaims2019$Motor.Net.Incurred, main = "", xlab = "2019 Motor Vehicle Claims")
```




```
# e
AutoClaimsGT10$Excess0 <- 1 * (AutoClaimsGT10$Excess == 0)
AutoClaimsGT10$ExcessLT1000 <- 1 * (AutoClaimsGT10$Excess < 1000) * (AutoClaimsGT10$Ex
    0)
AutoClaimsGT10$ExcessEq1000 <- 1 * (AutoClaimsGT10$Excess == 1000)
AutoClaimsGT10$ExcessGT1000 <- 1 * (AutoClaimsGT10$Excess > 1000)
AutoClaimsGT10$Constant1 <- AutoClaimsGT10$Excess0 * 0 + 1
library(doBy)
T1 <- summaryBy(Excess0 ~ UW.Year, data = AutoClaimsGT10, FUN = function(x) {
    m = sum(x, na.rm = TRUE)
})
T2 <- summaryBy(ExcessLT1000 ~ UW.Year, data = AutoClaimsGT10, FUN = function(x) {
    m = sum(x, na.rm = TRUE)
})
T3 <- summaryBy(ExcessEq1000 ~ UW.Year, data = AutoClaimsGT10, FUN = function(x) {
    m = sum(x, na.rm = TRUE)
})
T4 <- summaryBy(ExcessGT1000 ~ UW.Year, data = AutoClaimsGT10, FUN = function(x) {
    m = sum(x, na.rm = TRUE)
})
T5 <- summaryBy(Constant1 ~ UW.Year, data = AutoClaimsGT10, FUN = function(x) {
    m = sum(x, na.rm = TRUE)
})
TableOut <- cbind(T1, T2[2], T3[2], T4[2], T5[2])
colnames(TableOut) <- c("UW.Year", "Num 0", "Num 0-1000", "Num = 1000", "Num >1000",
    "Total")
```

Table 1.18: **Motor Vehicle Excess by Year**

UW.Year	Num 0	Num 0-1000	Num = 1000	Num >1000	Total
2011	1	1	7	0	9
2012	1	2	13	0	16
2013	4	1	22	0	27
2014	0	0	11	0	11
2015	1	1	14	0	16
2016	6	1	19	0	26
2017	16	0	4	1	21
2018	19	0	1	0	20
2019	99	0	6	0	105
2020	5	0	0	0	5
2021	10	0	0	0	10

```
knitr::kable(TableOut, align = "cccccccc", caption = "**Motor Vehicle Excess by Year**")
```

We provide summaries of this information simply so that readers can see what type of data are available for more in-depth analysis. Specifically, in addition to incurred losses, we also have the following information

```
knitr::kable(summary(AutoClaims)[, -1])
```

	Loss.Date	Reported.Date	Motor.Fault	Driver.Age	Vehicle.Description	Loss.Postcode
	Length:318	Length:318	Length:318	Min. :18.00	Length:318	Min. : 200
	Class :character	Class :character	Class :character	1st Qu.:28.00	Class :character	1st Qu.:2559
	Mode :character	Mode :character	Mode :character	Median :40.00	Mode :character	Median :2601
	NA	NA	NA	Mean :41.26	NA	Mean :2669
	NA	NA	NA	3rd Qu.:55.00	NA	3rd Qu.:2609
	NA	NA	NA	Max. :69.00	NA	Max. :7320
	NA	NA	NA	NA's :145	NA	NA's :3

```
# %>% kableExtra::kable_classic(font = 8, html_font = 'Cambria')
```

1.5 Further Resources and Contributors

Contributor

- **Edward (Jed) Frees**, University of Wisconsin-Madison, is the principal author of the initial version of this chapter.

- Chapter reviewers include: Yair Babad, Chunsheng Ban, Aaron Bruhn, Gordon Enderle, Hirokazu (Iwahiro) Iwasawa, Dalia Khalil, Bell Ouelega, Michelle Xia.
- **Edward (Jed) Frees**, University of Wisconsin-Madison and Australian National University, is the author of the second edition of this chapter. Email: jfrees@bus.wisc.edu for chapter comments and suggested improvements.

This book introduces loss data analytic tools that are most relevant to actuaries and other financial risk analysts. We have also introduced you to many new insurance terms; more terms can be found at the NAIC Glossary (2018). Here are a few references cited in the chapter.

Chapter 2

Appendix. Data Resources

This appendix section describes the datasets used in this book and others that you may wish to explore.

For each set of data, we provide download buttons so that you can easily access the data in standard .csv (comma separated value) format. This allows you replicate and experiment with the methods developed in the book as well as sharpen your understanding through exercises.

We provide the source of each dataset. We also recommend, for deeper understanding, that you occasionally refer to these original sources to further develop your appreciation of the data underpinning the analytics developed in this book.

2.1 Wisconsin Property Fund

Description: The Wisconsin Local Government Property Insurance Fund (LGPIF) is an insurance pool administered by the Wisconsin Office of the Insurance Commissioner. The LGPIF was established to provide property insurance for local government entities that include counties, cities, towns, villages, school districts, and library boards. The fund insures local government property such as government buildings, schools, libraries, and motor vehicles. It covers all property losses except those resulting from flood, earthquake, wear and tear, extremes in temperature, mold, war, nuclear reactions, and embezzlement or theft by an employee.

The data are available using this download button: Download the Wisconsin Property Fund Data

Table 2.1: **Variables in the Wisconsin Property Fund Dataset**

Variable	Description
PolicyNum	Policy number
Year	Contract year
Premium	Premium
Deduct	Deductible
BCcov	Coverage for building and contents
Freq	Number of claims during the year (frequency)
Fire5	Binary variable to indicate the fire class is below 5
NoClaimCredit	Binary variable to indicate no claims in the past two years
EntityType	Categorical variable that is one of six types: 1=Village, 2=City,3=County, 4=Misc,
AlarmCredit	Categorical variable that is one of four types: (0, 5, 10, or 15) for automatic smoke a
BCClaim	Builing and contents claims

Table 2.2: **Wisconsin Property Fund First Five Rows**

PolicyNum	Year	Premium	Deduct	BCcov	Freq	Fire5	NoClaimCredit	EntityType
120002	2006	9313	1000	22714456	0	1	0	3
120002	2007	8767	1000	25046646	0	1	0	3
120002	2008	7090	1000	20851525	0	1	1	3
120002	2009	8522	1000	21852696	0	1	1	3
120002	2010	7994	1000	23511493	1	1	1	3

Table 2.3: **Wisconsin Property Fund Last Five Rows**

PolicyNum	Year	Premium	Deduct	BCcov	Freq	Fire5	NoClaimCredit	EntityType
180787	2010	199	5e+02	285000	0	1	1	4
180788	2010	58344	1e+05	416739800	1	1	0	4
180789	2010	295	5e+02	500988	1	1	0	4
180790	2010	2077	1e+03	3580665	0	1	0	4
180791	2010	81	5e+02	118800	0	1	0	4

Table 2.4: **Variables in the Corporate Travel Dataset**

Variable	Description
UW Year	Underwriting Year
Loss Date	Date that the loss occurred
Reported Date	Date that the loss was reported
Last Trans Date	Last date in which there was a transaction regarding the loss
Paid Loss	Cumulative amount paid on the loss
Outstanding Reserve	Estimate of the loss amount yet to be paid
Incurred Loss	Sum of the amount paid and the estimate of future payments
Status	An indicator as to whether the claim has been deemed settled (closed) or not settled (oper

Table 2.5: **Corporate Travel Data First Five Rows**

UW.Year	Loss.Date	Reported.Date	Last.Trans.Date	Paid.Loss	Outstanding.Reserve	Incurred.Loss
2021	19/12/2021	20/12/2021	24/12/2021	10000.00	0	10000.00
2021	9/4/2022	29/04/2022	30/05/2022	423.08	0	423.08
2021	2/5/2022	4/5/2022		0.00	500	500.00
2021	5/5/2022	17/05/2022		0.00	562	562.00
2021	30/04/2022	27/05/2022	10/6/2022	1500.00	0	1500.00

2.2 ANU Corporate Travel Data

Universities purchase corporate travel policies to cover employees and students traveling on official university business for a wide variety of accidents and incidents while away from the campus or primary workplace. This broad coverage includes medical care and evacuation, loss of personal property, extraction for political and weather related reasons, and more. See Frees and Butt (2022) for more information about this coverage.

There are 2107 observations in this dataset. The variable names are described in Table 2.4 and the first and last five observations are in Table 2.6.

Data are available using this button: Download Corporate Travel Claims Data.

Table 2.6: **Corporate Travel Data Last Five Rows**

UW.Year	Loss.Date	Reported.Date	Last.Trans.Date	Paid.Loss	Outstanding.Reserve	Incurred.Loss
2006	1/11/2006	19/06/2007		0.00	0	0.00
2006	24/06/2007	26/06/2007	8/1/2008	6278.10	0	6278.10
2006	4/7/2007	6/7/2007	11/9/2007	114.50	0	114.50
2006	20/05/2007	26/06/2007	14/07/2007	135.65	0	135.65
2006	15/02/2007	27/06/2007	14/07/2007	1207.75	0	1207.75

Table 2.7: **Variables in the Group Personal Accident Dataset**

Variable	Description
UW Year	Underwriting Year
Loss Date	Date that the loss occurred
Last Trans Date	Last date in which there was a transaction regarding the loss.
Paid Loss	Cumulative amount paid on the loss
Outstanding Reserve	Estimate of the loss amount yet to be paid
Incurred Loss	Sum of the amount paid and the estimate of future payments
Status	An indicator as to whether the claim has been deemed settled (closed) or not s

Table 2.8: **Group Personal Accident Data First Five Rows**

UW.Year	Loss.Date	Last.Trans.Date	Paid.Loss	Outstanding.Reserve	Incurred.Loss	Statu
2021	6/12/2021	3/6/2022	805.0	0.0	805	Clos
2021	15/11/2021		0.0	0.0	0	Clos
2021	15/11/2021		0.0	0.0	0	Clos
2021	22/03/2022	4/5/2022	396.0	0.0	396	Clos
2021	11/4/2022	2/8/2022	740.1	359.9	1100	Ope

Source: Frees, Edward and Butt, Adam (2022). “ANU Corporate Travel Insurance Claims 2022”. Australian National University Data Commons. DOI https://doi.org/10.25911/vrdw-9f32.

2.3 ANU Group Personal Accident Data

Group personal accident insurance offers financial protection in case of injury or death resulting from an incident that occurs on the job. Like workers’ compensation, group personal accident offers insurance coverage and liability insurance protection against accidental death or injury. Unlike workers’ compensation, group personal accident covers students and ANU’s voluntary workers. See Frees and Butt (2022) for more information about this coverage.

There are 148 observations in this dataset. The variable names are described in Table 2.7 and the first and last five observations are in Table 2.9.

Data are available using this button: Download Group Personal Accident Claims Data.

Source: Frees, Edward and Butt, Adam (2022). “ANU Group Personal Accident Claims 2022”. Australian National University Data Commons. https://doi.org/10.25911/jcfx-zj56.

Table 2.9: **Group Personal Accident Data Last Five Rows**

UW.Year	Loss.Date	Last.Trans.Date	Paid.Loss	Outstanding.Reserve	Incurred.Loss	Status
2010	6/3/2011	26/07/2011	776.00	0	776.00	Closed
2010	22/07/2011	23/01/2012	4624.54	0	4624.54	Closed
2010	5/6/2011	30/01/2012	1503.65	0	1503.65	Closed
2007	11/1/2008	23/02/2008	0.00	0	0.00	Closed
2007	29/08/2008		0.00	0	0.00	Closed

Table 2.10: **Variables in the Motor Vehicle Dataset**

Variable	Description
Policy Term Start Date	Start date of the contract year in which the loss occurred
Loss Date	Date that the loss occurred
Reported Date	Date that the loss was reported
Motor Fault	Party responsible for the loss
Driver Age	Age of the driver
Vehicle Description	Type of vehicle
Loss Postcode	Postal code where the loss occurred
Excess	The deductible applied to the loss
Motor Net Paid	Amount paid to the insured (ANU)
Outstanding Estimate	Estimate of the loss amount yet to be paid
Motor Net Incurred	Sum of the amount paid and the estimate of future payments
Third Party Identified	Indicates whether a responsible third party could be identified
Third Party Insured	Indicates whether a responsible third party was insured

2.4 ANU Motor Vehicle Data

This policy covers ANU's vehicles including cars, vans, utilities, and motorcycles. See Frees and Butt (2022) for more information about this coverage.

There are 318 observations in this dataset. The variable names are described in Table 2.10 and the first and last five observations are in Table 2.12.

Data are available using this button: Download Motor Vehicle Claims Data.

Excess	Motor.Net.Paid	Outstanding.Estimate	Motor.Net.Incurred	Third.Party.Identified	Third.Party.Ins
1000	384.88	0	384.88	IDENTIFIED	
1000	901.21	0	901.21		
1000	1225.71	0	1225.71		
NA	1671.76	0	1671.76	IDENTIFIED	NOT INSUR
1000	3418.86	0	3418.86		INSURED

Table 2.11: **Motor Vehicle Data First Five Rows**

Policy.Term.Start.Date	Loss.Date	Reported.Date	Motor.Fault	Driver.A
1/11/2011	6/6/2012	4/10/2012	THIRD PARTY RESPONSIBLE	NA
1/11/2011	16/08/2012	14/11/2013	INSURED RESPONSIBLE	39
1/11/2011	4/9/2012	17/01/2013	INSURED RESPONSIBLE	52
1/11/2011	21/09/2012	28/09/2012	THIRD PARTY RESPONSIBLE	59
1/11/2011	22/09/2012	12/10/2012	INSURED RESPONSIBLE	NA

Table 2.12: **Motor Vehicle Data Last Five Rows**

Policy.Term.Start.Date	Loss.Date	Reported.Date	Motor.Fault	Driver.Age	
1/11/2021	4/4/2022	5/4/2022	INSURED RESPONSIBLE	66	V
11/1/2021	11/4/2022	9/5/2022	INSURED RESPONSIBLE	27	
1/11/2021	11/4/2022	9/5/2022	INSURED RESPONSIBLE	27	
11/1/2021	15/04/2022	11/7/2022	INSURED RESPONSIBLE	21	
1/11/2021	18/07/2022	18/07/2022	NO-ONE RESPONSIBLE	NA	

Excess	Motor.Net.Paid	Outstanding.Estimate	Motor.Net.Incurred	Third.Party.Identified	Th
0	2373.49	1056.00	3429.49		
0	210.00	25000.00	25210.00		
0	0.00	31927.27	31927.27		
0	0.00	2750.00	2750.00		
0	0.00	299.00	299.00		

Source: Frees, Edward and Butt, Adam (2022). "ANU Motor Vehicle Claims 2022". Australian National University Data Commons. DOI https://doi.org/10.25911/g7e4-9e46.

2.5 Spanish Personal Insurance Data

This dataset consists of 10,000 insurance private customers of a real portfolio of insurance policy holders in Spain with a motor insurance and a homeowners insurance contract for policy year 2014. The data contain information on each customer, policies and yearly claims by type of contract.

The data are available using this download button: Download the Spanish Personal Insurance Data

The description of the data is the following:

All monetary units are expressed in Euros. In motor insurance, only claims at fault are considered.

Table 2.13: Variable and Description of Spanish Personal Insurance Data

Variable	Description
gender	1 for male and 0 for female
Age_client	the age of the customer in years
year	Policy year. Equals 5 corresponding to 2014.
age_of_car_M	the number of years since the vehicle was bought by the customer
Car_power_M	the power of the vehicle
Car_2ndDriver_M	1 if the customer has informed the insurance company that a second occasional dri
num_policiesC	the total number of policies held by the same customer in the insurance company
metro_code	1 for urban or metropolitan and 0 for rural
Policy_PaymentMethodA	1 for annual payment and 0 for monthly payment in the motor policy
Policy_PaymentMethodH	1 for annual payment and 0 for monthly payment in the homeowners policy
Insuredcapital_content_re	the value of content in homeowners insurance
Insuredcapital_continent_re	the value of building in homeowners insurance
appartment	1 if the homeowners insurance correspond to an apartment and 0 otherwise
Client_Seniority	the number of years that the customer has been in the company
Retention	1 if the policy is renewed and 0 otherwise
NClaims1	the number of claims in the motor insurance policy for the corresponding year
NClaims2	the number of claims in the homeowners insurance policy for the corresponding yea
Claims1	the sum of claims cost in the motor insurance policy for the corresponding year
Claims2	the sum of claims cost in the homeowners insurance policy for the corresponding y
Types	1 when neither an auto nor a home claim, it is equal to 2 when the customer has a
PolID	Policy Identification Number

Table 2.14: **Spanish Personal Insurance Data First Five Rows**

gender	Age_client	year	age_of_car_M	Car_power_M	Car_2ndDriver_M	num_policiesC	metro_c
1	47	5	12	163	0	0	0
1	52	5	13	80	0	1	0
0	66	5	7	97	0	1	1
1	70	5	17	95	0	1	0
1	67	5	13	110	0	1	0

Table 2.15: **Spanish Personal Insurance Data Last Five Rows**

gender	Age_client	year	age_of_car_M	Car_power_M	Car_2ndDriver_M	num_policies
1	66	5	8	143	0	1
1	55	5	18	125	1	1
0	41	5	10	190	0	1
1	50	5	5	140	0	1
1	55	5	12	90	0	1

Insuredcapital_content_re	Insuredcapital_continent_re	appartment	Client_Seniority	Retent
10.189202	12.07322	1	6.581793	1
9.571442	11.44319	0	18.480493	1
9.330216	11.27605	1	15.085558	1
10.484897	11.13662	1	15.523614	1
10.961310	12.34759	0	6.108145	1

Insuredcapital_content_re	Insuredcapital_continent_re	appartment	Client_Seniority	Retent
10.305182	11.40377	1	19.731691	1
10.888420	11.07072	1	15.334702	1
9.224866	11.63272	1	6.006845	1
9.969163	12.27171	0	8.391513	1
11.127278	12.73670	0	6.422998	1

These data were drawn from a larger database of 40,284 insurance private customers. These customers are tracked from 2010 to 2014. Some customers do not renew their policies, so that they do not stay in the sample for five years. For the smaller data, only the 2014 policy year was used and from this, a random sample of 10,000 customers was drawn.

See Frees et al. (2021) for more information about this dataset. The larger database contains 122935 rows and is freely available at:

Source:

Guillen, Montserrat; Bolancé, Catalina; Frees, Edward W.; Valdez, Emiliano A. (2021), "Insurance data for homeowners and motor insurance customers monitored over five years", Mendeley Data, V1, DOI https://doi.org/10.17632/vfchtm5y7j.1

2.6 'R' Package CASdatasets

The `R` package `CASdatasets` provides a convenient way to access many well-known insurance datasets. This package was originally created to support the book *Computational Actuarial Science with R*, edited by Arthur Charpentier, Charpentier (2014).

To install the package, here is a bit of `R` code:

```
install.packages("CASdatasets", repos = "http://cas.uqam.ca/pub/", type = "source")
library(CASdatasets)
`?`(CASdatasets)
`?`(sgautonb  # See the documentation of the Singapore Auto Data
)
`?`(lossalae  # See the documentation of the Loss and Expense Data
)
```

Note that this package assumes that you have already installed a few other packages, including *xts*, *sp*, and *zoo*.

To illustrate,

- in Chapter 4 we use the Singapore data (referred to as `sgautonb` in the package) and
- in Chapter 15 we use the loss and expense data (referred to as `lossalae` in the package).

2.7 Other Data Sources

There exists man other (non-actarial) data sources. First, data can be obtained from university-based researchers who collect primary data. Second, data can be obtained from organizations that are set up for the purpose of releasing secondary data for the general research community. Third, data can be obtained from national and regional statistical institutes that collect data. Finally, companies have corporate data that can be obtained for research purposes.

While it might be difficult to obtain data to address a specific research problem or answer a business question, it is relatively easy to obtain data to test a model or an algorithm for data analysis. In the modern era, readers can obtain datasets from the Internet. The following is a list of some websites to obtain real-world data:

- **UCI Machine Learning Repository.** This website (url: http://archive.ics.uci.edu/ml/index.php) maintains more than 400 datasets that can be used to test machine learning algorithms.
- **Kaggle.** The Kaggle website (url: https://www.kaggle.com/) include real-world datasets used for data science competitions. Readers can download data from Kaggle by registering an account.
- **DrivenData.** DrivenData aims at bringing cutting-edge practices in data science to solve some of the world's biggest social challenges. In its website (url: https://www.drivendata.org/), readers can participate in data science competitions and download datasets.
- **Analytics Vidhya.** This website (url: https://datahack.analyticsvidhya.com/contest/all/) allows you to participate and download datasets from practice problems and hackathon problems.

- **KDD Cup.** KDD Cup is the annual Data Mining and Knowledge Discovery competition organized by the ACM Special Interest Group on Knowledge Discovery and Data Mining. This website (url: http://www.kdd.org/kdd-cup) contains the datasets used in past KDD Cup competitions since 1997.
- **U.S. Government's open data.** This website (url: https://www.data.gov/) contains about 200,000 datasets covering a wide range of areas including climate, education, energy, and finance.
- **AWS Public Datasets.** In this website (url: https://aws.amazon.com/datasets/), Amazon provides a centralized repository of public datasets, including some huge datasets.

Chapter 3

Glossary

Term	Definition
analytics	Analytics is the process of using data to make decisions.
renters insurance	Renters insurance is an insurance policy that covers the contents of an apartment or house that you are renting.
automobile insurance	An insurance policy that covers damage to your vehicle, damage to other vehicles in the accident, as well as medical expenses of those injured in the accident.
casualty insurance	Causalty insurance is a form of liability insurance providing coverage for negligent acts and omissions. examples include workers compensation, errors and omissions, fidelity, crime, glass, boiler, and various malpractice coverages.
commercial insurance	
term	The duration of an insurance contract
insurance claim	An insurance claim is the compensation provided by the insurer for incurred hurt, loss, or damage that is covered by the policy.
homeowners insurance	Homeowners insurance is an insurance policy that covers the contents and property of a building that is owned by you or a friend.
property insurance	Property insurance is a policy that protects the insured against loss or damage to real or personal property. the cause of loss might be fire, lightening, business interruption, loss of rents, glass breakage, tornado, windstorm, hail, water damage, explosion, riot, civil commotion, rain, or damage from aircraft or vehicles.
non-life	Non-life insurance is any type of insurance where payments are not based on the death (or survivorship) of a named insured. examples include automobile, homeowners, and so on. also known as property and casualty or general insurance.

life insurance	Life insurance is a contract where the insurer promises to pay upon the death of an insured person. the person being paid is the beneficiary.
personal insurance	Insurance purchased by a person
loss adjustment expenses	Loss adjustment expenses are costs to the insurer that are directly attributable to settling a claims. for example, the cost of an adjuster is someone who assess the claim cost or a lawyer who becomes involve in settling an insurer's legal obligation on a claim
unallocated	Unallocated loss adjustment expenses are costs that can only be indirectly attributed to claim settlement; for example, the cost of an office to support claims staff
allocated	Allocated loss adjustment expenses, sometimes known by the acronym alea, are costs that can be directly attributed to settling a claim; for example, the cost of an adjuster
underwriting	Underwriting is the process where the company makes a decision as to whether or not to take on a risk.
loss reserving	A loss reserve is an estimate of liability indicating the amount the insurer expects to pay for claims that have not yet been realized. this includes losses incurred but not yet reported (ibnr) and those claims that have been reported claims that haven't been paid (known by the acronym rbns for reported but not settled).
risk classification	Risk classification is the process of grouping policyholders into categories, or classes, where each insured in the class has a risk profile that is similar to others in the class.
retrospective premiums	The process of determining the cost of an insurance policy based on the actual loss experience determined as an adjustment to the initial premium payment.
claims adjustment	Claims adjustment is the process of determining coverage, legal liability, and settling claims.
claims leakage	Claims leakage respresents money lost through claims management inefficiencies.
adjuster	An adjuster is a person who investigates claims and recommends settlement options based on estimates of damage and insurance policies held.
dividends	A dividend is the refund of a portion of the premium paid by the insured from insurer surplus.
indemnification	Indemnification is the compensation provided by the insurer.
rating variables	Rating variables are the components of an insurance pricing formula. they can include numeric variables (like values, revenue, or area) and classification variables (like location, type of vehicle, or type of occupancy.)
frequency	Count random variables that represent the number of claims
severity	The amount, or size, of each payment for an insured event

probability mass function (pmf)	A function that gives the probability that a discrete random variable is exactly equal to some value
distribution function	The chance that the random variable is less than or equal to x, as a function of x
mean	Average
moments	The rth moment of a list is the average value of the random variable raised to the rth power
survival function	The probability that the random variable takes on a value greater than a number x
moment generating function (mgf)	The mgf of random variable n is defined the expectation of exp(tn), as a function of t
probability generating function (pgf)	For a random variable n, its pgf is defined as the expectation of s^n, as a function of s
convex hulls	The convex hull of a set of points x is the smallest convex set that contains x
risk classes	The formation of different premiums for the same coverage based on each homogeneous group's characteristics.
binomial distribution	A random variable has a binomial distribution (with parameters m and q) if it is the number of "successes" in a fixed number m of independent random trials, all of which have the same probability q of resulting in "success."
binary outcomes	Outcomes whose unit can take on only two possible states, traditionally labeled as 0 and 1
m-convolution	The addition of m independent random variables
poisson distribution	A discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time or space if these events occur with a known constant rate and independently of the time since the last event
negative binomial distribution	The number of successes until we observe the rth failure in independent repetitions of an experiment with binary outcomes
overdispersed	The presence of greater variability (statistical dispersion) in a data set than would be expected based on a given statistical model
underdispersed	There was less variation in the data than predicted
(a, b, 0) class	The poisson, binomial and negative binomial distributions
maximum likelihood estimator (mle)	The possible value of the parameter for which the chance of observing the data largest
local extrema	The largest and smallest value of the function within a given range
central limit theorem (clt)	In some situations, when independent random variables are added, their properly normalized sum tends toward a normal distribution even if the original variables themselves are not normally distributed.
newton's method	A root-finding algorithm which produces successively better approximations to the roots of a real-valued function

robust	Resistant to errors in the results, produced by deviations from assumptions
explanatory variables	In regression, the explanatory variable is the one that is supposed to ”explain” the other.
regression analysis	A set of statistical processes for estimating the relationships among variables
homogeneous	Units of exposure that face approximately the same expected frequency and severity of loss.
(a,b,1)	A count distribution with probabilities satisfying p__k/p__{k-1}=a+b/k, for some some constants a and b and k>=2
zero truncation	Zero modification of a count distribution such that it assigns zero probability to zero count
degenerate distribution	A deterministic distribution and takes only a single value
convex combination	A linear combination of points where all coefficients are non-negative and sum to 1
convex function	A real-valued function defined on an interval is called convex if the line segment between any two points on the graph of the function lies above or on the graph.
mixture distribution	The probability distribution of a random variable that is derived from a collection of other random variables as follows: first, a random variable is selected by chance from the collection according to given probabilities of selection, and then the value of the selected random variable is realized
chi-square distribution	The chi-squared distribution with k degrees of freedom is the distribution of a sum of the squares of k independent standard normal random variables
aic	A goodness of fit measure of a statistical model that describes how well it fits a set of observations.
pearson’s chi-square test	A statistical test applied to sets of categorical data to evaluate how likely it is that any observed difference between the sets arose by chance
multinomial likelihood	The multinomial distribution models the probability of counts for rolling a k-sided die n times
aggregate losses	Aggregate claims, or total claims observed in the time period
liability insurance	Insurance that compensates an insured for loss due to legal liability towards others
mixture distribution	A weighted average of other distributions, which may be continuous or discrete
continuous random variable	Random variable which can take infinitely many values in its specified domain
raw moment	The kth moment of a random variable x is the average (expected) value of x^k

central moment	The kth central moment of a random variable x is the expected value of (x-its mean)^k
skewness	Measure of the symmetry of a distribution, 3rd central moment/standard deviation^3
kurtosis	Measure of the peaked-ness of a distribution, 4th central moment/standard deviation^4
expected value	Average
exponential distribution	A single parameter continous probability distribution that is defined by its rate parameter
independent	Two variables are independent if conditional information given about one variable provides no information regarding the other variable
percentile	The pth percentile of a random variable x is the smallest value x_p such that the probability of not exceeding it is p%
chi-square distribution	A common distribution used in chi-square tests for determining goodness of fit of observed data to a theorized distribution
light tailed distribution	A distribution with thinner tails than the benchmark exponential distribution
pareto distribution	A heavy-tailed and positively skewed distribution with 2 parameters
hazard function	Ratio of the probability density function and the survival function: f(x)/s(x), and represents an instantaneous probability within a small time frame
weibull distribution	A positively skewed continuous distribution with 2 parameters that can have an increasing or decreasing hazard function depending on the shape parameter
generalized beta distribution of the second kind	A 4-parameter flexible distribution that encompasses many common distributions
parametric distributions	Probability distribution defined by a fixed set of parameters
transformation	A function or method that turns one distribution into another
distribution function technique	A transformation technique that involves finding the cdf of the transformed distribution through its relation with the original cdf
change-of-variable technique	A transformation technique that involves finding the pdf of the transformed distribution through its relation with the original pdf using inverse functions
moment-generating function technique	A transformation technique that uses moment generating functions properties to determine the mgf of a linear combination of variables
lognormal distribution	A heavy-tailed, positively skewed 2-parameter continuous distribution such that the natural log of the random variable is normally distributed with the same parameter values
reliability data	A dataset consisting of failure times for failed units and run times for units still functioning
power transformation	A transformation type that involves raising a random variable to a power

exponential transformation	A transformation type that involves raising a random variable in the exponent
mixing parameters	Proportion weight given to each subpopulation in a mixture
heterogeneous population	A dataset where the subpopulations are represented by separate distinct distributions
finite mixture	A mixture distribution with a finite k number of subpopulations
continuous mixture	A mixture distribution with an infinite number of subpopulations, where the mixing parameter is itself a continuous distribution
conditional distribution	A probability distribution that applies to a subpopulation satisfying the condition
unconditional distribution	A probability distribution independent of any another imposed conditions
prior distribution	A probability distribution assigned prior to observing additional data
scale distribution	A distribution with the property that multiplying all values by a constant leads to the same distribution family with only the scale parameter changed
moral hazard	Situation where an insured is more likely to be risk seeking if they do not bear sufficient consequences for a loss
payment per loss	Amount insurer pays when a loss occurs and can be 0
payment per payment	Amount insurer pays given a payment is needed and is greater than 0
left censored	Values below a threshold d are not ignored but converted to 0
left truncated	Values below a threshold d are not reported and unknown
loss elimination ratio (ler)	% decrease of the expected payment by the insurer as a result of the deductible
franchise deductible	Insurer pays nothing for losses below the deductible, but pays the full amount for any loss above the deductible
limit of coverage	Policy limit, or maximum contractual financial obligation of the insurer for a loss
group insurance	Insurance provided to groups of people to take advantage of lower administrative costs vs. individual policies
growth factor	Multiplicative factor applied to a distribution to account for the impact of inflation, typically (1+rate)
cedent	Party that is transferring the risk to a reinsurer
excess of loss coverage	Contract where an insurer pays all claims up to a specified amount and then the reinsurer pays claims in excess of stated reinsurance deductible
retention	Maximum amount payable by the primary insurer in a reinsurance arrangement
right censored variable	Values above a threshold u are not ignored but converted to u
reinsurance	A transaction where the primary insurer buys insurance from a re-insurer who will cover part of the losses and/or loss adjustment expenses of the primary insurer

method of maximum likelihood	Statistical method used to derive the parameter values from data that maximize the probability of observing the data given the parameters
grouped data	Data bucketed into categories with ranges, such as for use in histograms or frequency tables
large-sample properties	Asymptotic properties of a distribution as the amount of data increases towards infinity
asymptotic variance	Variability of the distribution of an estimator as the amount of data increases towards infinity
delta method	Statistical method used to approximate the asymptotic variance for a function based on parameters whose asymptotic variance can be determined
log-likelihood function	Natural log of the likelihood function
covariance matrix	Matrix where the (i,j)^th element represents the covariance between the ith and jth random variables
complete data	Data where each individual observation is known, and no values are censored, truncated, or grouped
parametric	Distributional assumptions made on the population from which the data is drawn, with properties defined using parameters.
nonparametric	No distributional assumptions are made on the population from which the data is drawn.
sampling scheme	How the data is obtained from the population and what data is observed.
unbiased	An estimator that has no bias, that is, the expected value of an estimator equals the parameter being estimated.
plug-in principle	The plug-in principle or analog principle of estimation proposes that population parameters be estimated by sample statistics which have the same property in the sample as the parameters do in the population.
indicator	A categorical variable that has only two groups. the numerical values are usually taken to be one to indicate the presence of an attribute, and zero otherwise. another name for a binary variable.
empirical distribution function	The empirical distribution is a non-parametric estimate of the underlying distribution of a random variable. it directly uses the data observations to construct the distribution, with each observed data point in a size-n sample having probability 1/n.
first quartile	The 25th percentile; the number such that approximately 25% of the data is below it.
third quartile	The 75th percentile; the number such that approximately 75% of the data is below it.
quantile	The q-th quantile is the point(s) at which the distribution function is equal to q, i.e. the inverse of the cumulative distribution function.
smoothed empirical quantile	A quantile obtained by linear interpolation between two empirical quantiles, i.e. data points.

bandwidth	A small positive constant that defines the width of the steps and the degree of smoothing.
kernel density estimator	A nonparametric estimator of the density function of a random variable.
bias-variance tradeoff	The tradeoff between model simplicity (underfitting; high bias) and flexibility (overfitting; high variance).
model diagnostics	Procedures to assess the validity of a model
probability-probability (pp) plot	A plot that compares two models through their cumulative probabilities.
quantile-quantile (qq) plot	A plot that compares two models through their quantiles.
goodness of fit	A measure used to assess how well a statistical model fits the data, usually by summarizing the discrepancy between the observations and the expected values under the model.
method of moments	The estimation of population parameters by approximating parametric moments using empirical sample moments.
percentile matching	The estimation of population parameters by approximating parametric percentiles using empirical quantiles.
percentile	A 100p-th percentile is the number such that 100 times p percent of the data is below it.
gini index	A measure for assessing income inequality. it measures the discrepancy between the income and population distributions and is calculated from the lorenz curve.
model selection	The process of selecting a statistical model from a set of candidate models using data.
in-sample	A dataset used for analysis and model development. also known as a training dataset.
out-of-sample	A dataset used for model validation. also known as a test dataset.
cross-validation	A model validation procedure in which the data sample is partitioned into subsamples, where splits are formed by separately taking each subsample as the out-of-sample dataset.
model validation	The process of confirming that the proposed model is appropriate.
data-snooping	Repeatedly fitting models to a data set without a prior hypothesis of interest.
predictive inference	Preditive inference is the process of using past data observations to predict future observations.
likelihood function	A function of the likeliness of the parameters in a model, given the observed data.
ogive estimator	A nonparametric estimator for the distribution function in the presence of grouped data.
product-limit estimator	A nonparametric estimator of the survival function in the presence of incomplete data. also known as the kaplan-meier estimator.
risk set	The number of observations that are active (not censored) at a specific point.

nelson-aalen	A nonparametric estimator of the cumulative hazard function in the presence of incomplete data.
credibility	An actuarial method of balancing an individual's loss experience and the experience in the overall portfolio to improve ratemaking estimates.
bayesian	A type of statistical inference in which the model parameters and the data are random variables.
predictive distribution	The distribution of new data, conditional on a base set of data, under the bayesian framework.
least squares	A technique for estimating parameters in linear regression. it is a standard approach in regression analysis to the approximate solution of overdetermined systems. in this technique, one determines the parameters that minimize the sum of squared differences between each observation and the corresponding linear combination of explanatory variables.
markov chain monte carlo (mcmc) simulation	The class of numerical methods that use markov chains to generate draws from a posterior distribution.
improper prior	A prior distribution in which the sum or integral of the distribution is not finite.
confidence interval	Another term for interval estimate. unlike a point estimate, it gives a range of reliability for approximating a parameter of interest.
decision analysis	Bayesian decision theory is the study of an agent's choices, which is informed by bayesian probability.
conjugate distributions	Distributions such that the posterior and the prior come from the same family of distributions.
credibility interval	A summary of the posterior distribution of parameters under the bayesian framework.
prior distribution	The distribution of the parameters prior to observing data under the bayesian framework.
exposure	A measure of the rating units for which rates are applied to determine the premium. for example, exposures may be measured on a per unit basis (e.g. a family with auto insurance under one contract may have an exposure of 2 cars) or per $1,000 of value (e.g. homeowners insurance).
inflation	Inflation is a sustained increase in the general price level of goods and services over a period of time.
business line	
individual risk model	A modeling approach for aggregate losses in which the loss from each individual contract is considered.
collective risk model	A modeling approach for aggregate losses in which the aggregate loss is represented in terms of a frequency distribution and a severity distribution.

coverage	Insurance coverage is the amount of risk or liability that is covered for an individual or entity by an insurance policy.
frequency distribution	The random number of claims that occur under the collective risk model.
severity distribution	The randomly distributed amount of each loss under the collective risk model.
central limit theorem	Given certain conditions, the arithmetic mean of a large number of replications of independent random variables, each with a finite mean and variance, will be approximately normally distributed, regardless of the underlying distribution.
term life insurance	A term life insurance policy is payable only if death of the insured occurs within a specified time, such as 5 or 10 years, or before a specified age.
pure endowment	A pure endowment is an insurance policy that is payable at the end of the policy period if the insured is still alive. if the insured has died, there is nothing paid in the form of benefits.
support	The set of all outcomes for a random variable following some distribution. for example, exponentially distributed random variable x has support x>0.
convolution	The convolution of probability distributions is the distribution corresponding to the addition of independent random variables.
law of iterated expectations	A decomposition of the expected value of a random variable into conditional components. specifically, for random variables x and y, e(x) = e[e(x|y)].
compound distribution	A random variable follows a compound distribution if it is parameterized and contains at least one parameter that is itself a random variable. for example, the tweedie distribution is a compound distribution.
tweedie distribution	A compound distribution that is a poisson sum of gamma random variables. because it can accommodate a discrete probability mass at zero and a continuous positive component, it is suitable for modeling aggregate insurance claims.
shape parameter	A numerical parameter of a parametric distribution affecting the shape of a distribution rather than simply shifting it (as a location parameter does) or stretching/shrinking it (as a scale parameter does).
scale parameter	A numerical parameter of a parametric distribution that stretches/shrinks the distribution without changing its location or shape. the larger the scale parameter, the more spread out the distribution. the scale parameter is also the reciprocal of the rate parameter. for example, the normal distribution has scale parameter \sigma.

exponential dispersion	A set of distributions that represents a generalisation of the natural exponential family and also plays an important role in generalized linear models.
generalized linear models	Commonly known by the acronym glm. an extension of the linear regression model where the dependent variable is a member of the linear exponential family. glm encompasses linear, binary, count, and long-tailed, regressions all as special cases.
exponential family	A family of parametric distributions that are practical for modeling the underlying response variable in generalized linear models. this family includes the normal, bernoulli, poisson, and tweedie distributions as special cases, among many others.
monte carlo simulation	A computerized statistical model that simulates the effects of various types of uncertainty.
empirical distribution	The empirical distribution is a non-parametric estimate of the underlying distribution of a random variable. it directly uses the data observations to construct the distribution, with each observed data point in a size-n sample having probability 1/n.
converge	A type of stochastic convergence for a sequence of random variables x_1,..., x_n that approaches some other distribution as n approaches \infty.
policy limits	A policy limit is the maximum value covered by a policy.
ground-up loss	The total amount of loss sustained before policy adjustments are made (i.e. before deductions are applied for coinsurance, deductibles, and/or policy limits.)
per-loss basis	Due to policy modifications (e.g. deductibles), not all losses that occur result in payment. the per-loss basis considers every loss that occurs.
per-payment basis	Due to policy modifications (e.g. deductibles), not all losses that occur result in payment. the per-payment basis which considers only the losses that result in some payment to the insured.
memoryless	The memoryless property means that a given probability distribution is independent of its history and what has already elapsed. specifically, random variable x is memoryless if pr(x > s+t | x >= s) = pr(x > t). note that it does not mean x > s+t and x >= s are independent events.
central limit theorem	The sample mean and sample sum of a random sample of n from a population will converge to a normal curve as the sample size n grows
simulations	A computer generation of various hypothetical conditions and outputs, based on the model structure provided
linear congruential generator	Algorithm that yields pseudo-randomized numbers calculated using a linear recursive relationship and a starting seed value
pseudo-random numbers	Values that appear random but can be replicated by formula

inverse transform method	Samples a uniform number between 0 and 1 to represent the randomly selected percentile, then uses the inverse of the cumulative density function of the desired distribution to simulate from in order to find the simulated value from the desired distribution
quantile function	Inverse function for the cumulative density function which takes a percentile value in [0,1] as the input, and outputs the corresponding value in the distribution
greatest lower bound	Largest value that is less than or equal to a specified subset of values/elements
universal life insurance	Type of cash value life insurance where the policy's cash value is the excess of premium payments over the cost of insurance, accumulated with interest, with adjustable premiums and coverage over time
variable life insurance	Type of life insurance whose face value and coverage term can vary depending upon the performance of underlying invested securities
sampling variability	How much an estimate can vary between samples
cauchy distribution	A continuous distribution that represents the distribution of the ratio of two independent normally random variables, where the denominator distribution has mean zero
kolmogorov-smirnov test	A nonparametric statistical test used to determine if a data sample could come from a hypothesized continuous probability distribution
bootstrap	A method of sampling with replacement from the original dataset to create additional simulated datasets of the same size as the original
nonparametric approach	A statistical method where no assumption is made about the distribution of the population
parametric approach	A statistical method where a prior assumption is made about the distribution or model form
bias	The difference between the expected value of an estimator and the parameter being estimated. bias is an estimation error that does not become smaller as one observes larger sample sizes.
bias-corrected estimator	If an estimator is known to be consistently biased in a manner, it can be corrected using a factor to be come less biased or unbiased
jensen inequality	For a convex function f(x), f(expected value of x) <= expected value of f(x)
natural estimator	An estimator that uses the sample moments as the estimators for the population
percentile bootstrap interval	Confidence interval for the parameter estimates determined using the actual percentile results from the bootstrap sampling approach, as every bootstrap sample has an associated parameter estimate(s) that can be ranked against the others
k-fold cross-validation	A type of validation method where the data is randomly split into k groups, and each of the k groups is held out as a test dataset in turn, while the other k-1 gropus are used for distribution or model fitting, with the process repeated k times in total

leave-one-out cross validation	A special case of k-fold cross validation, where each single data point gets a turn in being the lone hold-out test data point, and n separate models in total are built and tested
jackknife statistics	To calculate an estimator, leave out each observation in turn, calculate the sample estimator statistic each time, and average over the n separate estimates
accept-reject mechanism	A sampling method that is used where the random sample is discarded if not within a certain pre-specified range [a, b] and is commonly used when the traditional inverse transform method cannot be easily used
importance sampling mechanism	Type of sampling method where values in the region of interest can be over-sampled or values outside the region of interest can be under-sampled
ergodic theorem	Ergodic theory studies the behavior of a dynamical system when it is allowed to run for an extended time
markov process	A stochastic (time dependent) process that satisfies memorylessness, meaning future predictions of the process can be made solely based on its present state and not the historical path
invariant measure	Any mathematical measure that is preserved by a function (the mean is an example)
composants	Component (smaller, self-contained part of larger entity)
hastings metropolis	A markov chain monte carlo (mcmc) method for random sampling from a probability distribution where values are iteratively generated, with the distribution of the next sample dependent only on the current sample value, and at each iteration, the candidate sample can be either accepted or rejected
gibbs sampler	A markov chain monte carlo (mcmc) method to obtain a sequence of random samples from a specified multivariate continuous probability distribution
premium	Amount of money an insurer charges to provide the coverage described in the policy
ratemaking	Process used by insurers to calculate insurance rates, which drive insurance premiums
insurance rates	Amount of money needed to cover losses, expenses, and profit per one unit of exposure
insured contingent event	A condition that results in an insurance claim
expected costs	The cost to an insurer of payments to the insured and allocated loss adjustment expenses (alaes). overhead and profit are not included
underwriting profit	Profit an insurer derives from providing coverage, excluding investment income
experience rating	A type of rating plan that uses the insured's historical loss experience as part of the premium determination
price	A quantity, usually of money, that is exchanged for a good or service

rates	A rate is the price, or premium, charged per unit of exposure. a rate is a premium expressed in standardized units.
technical prices	
loss cost	The sum of losses divided by an exposure; it is also known as the pure premium.
profit loading	A factor or percentage applied to the premium calculation to account for insurer profit in a policy
indicated change factor	A factor calculated from the loss ratio method that calculates how the rates should change, with factors > 1 indicating an increase and vice versa
indicated rate	In a rate filing, the amount that the loss experience suggests that the insurer should charge to cover costs.
credibility	Weight assigned to observed data vs. that assigned to an external or broader-based set of data
parametric distribution	Model assumption that the sample data comes from a population that can be modeled by a probability distribution with a fixed set of parameters
commercial business property	Line of business that insures against damage to their buildings and contents due to a covered cause of loss
continuous variables	Type of variable that can take on any real value
discrimination	Process of determining premiums on the basis of likelihood of loss. insurance laws prohibit ”unfair discrimination”.
rating factor	A rating factor, or rating variable, is a characteristic of the policyholder or risk being insured by which rates vary.
rating variable	A rating factor, or rating variable, is a characteristic of the policyholder or risk being insured by which rates vary.
factor	A variable that varies by groups or categories.
relativity	The difference of the expected risk between a specific level of a rating factor and an accepted baseline value. this difference may be arithmetic or proportional.
scale distribution	Suppose that y = c x, where x comes from a parametric distribution family and c is a positive constant. the distribution is said to be a scale distribution if (i) the distributions of y and x come from the same family and (ii) only a single parameter differs and that by a factor of c.
written exposures	Exposure is based off policies written/issued
earned exposures	Exposure is based off amount exposed to loss for which coverage has been provided
unearned exposures	Exposure amount for which coverage has not yet been provided
in force exposures	Exposure amount subject to loss at a particular point in time
calendar year method	Experience for rating is aggregated based on calendar year, as opposed to other methods such as when a policy term began
accident date	Date of loss occurrence that gives rise to a claim
report date	Date when insurer is notified of the claim

open claim	A claim that has been reported but not yet closed
mix of business	Different types of policies in an insurer's portfolio
on-level earned premium	Earned premium of historical policies using the current rate structure
experience loss ratio	Ratio of experience loss to on-level earned premium in the experience period
claim	The amount paid to an individual or corporation for the recovery, under a policy of insurance, for loss that comes within that policy.
incurred but not reported	A claim is said to be incurred but not reported if the insured event occurs prior to a valuation date (and hence the insurer is liable for payment) but the event has not been reported to the insurer.
closed	A claim is said to be closed when the company deems its financial obligations on the claim to be resolved.
valuation date	A valuation date is the date at which a company summarizes its financial position, typically quarterly or annually.
policy year	This is the period between a policy's anniversary dates.
gini index	The gini index is twice the area between a lorenz curve and a 45 degree line.
line of equality	45 degree line equating x and y, that represents a perfect alignment in the sample and population distribution
pp plot	Statistical plot used to assess how close a data sample matches a theorized distribution
performance curve	A concentration curve is a graph of the distribution of two variables, where both variables are ordered by only one of variables. for insurance applications, it is a graph of distribution of losses versus premiums, where both losses and premiums are ordered by premiums.
community rating	This generally refers to the premium principle where all risks pay the same amount.
market conduct regulation	Regulation that ensures consumers obtain fair and reasonable insurance prices and coverage
government prescribed	Government sets the entire rating system including coverages
prior approval	Regulator must approve rates, forms, rules filed by insurers before use
no file	Insurers may use new rates, forms, rules without approval from regulators
file only	Insurers must file rates, forms, rules for record keeping and use immediately
rating factors	Characteristics of a risk that help price the insurance contract
multiplicative tariff model	A rating method where each rating factor is the product of parameters associated with that rating factor
risk characteristics	The distinguishing features of a policy that help determine the expected loss on the policy

gross insurance premium	Sum of expected losses and expenses and profit on a policy
adverse selection	A pricing structure that entices riskier individuals to purchase and discourages low-risk individuals from purchasing
adverse selection spiral	Phenomenon where a book of business deteriorates as it attracts ever-riskier individuals when forced to increase premiums due to losses
a priori variables	Variables which the insurer has prior knowledge of before the policy inception
closed-form expressions	A mathematical expression that can be well defined with a formula that has a finite number of operations
levels	Different outcomes of a categorical variable
nominal	A categorical variable where the categories do not have a natural order and any numbering is arbitrary
dummy variables	A variable that takes on a value of 0 or 1 to indicate the absence or presence of a categorical characteristic
log linear form	Linear regression model where the response variable is the natural log of the expected response value
base case	The categorical level chosen as the default with all dummy variable indicators of 0
workers compensation	A no-fault insurance system prescribed by state law where benefits are provided by an employer to an employee due to a job-related injury, including death, resulting from an accident or occupational disease
exposure bases	The unit of measurement chosen to represent the exposure for a particular risk
offset	Natural log of the exposure amount that is added to a regression model to account for varying exposures
tariff	A table or list that contains the rating factors and associated premiums and other risk information
in-force times	The timeframe during which a policy is active and the insurer is bound by the contractual obligation
rate parameter	Parameter in certain distributions, such as the exponential, that indicate how quickly the function decays, and it is the reciprocal of the scale parameter
functional forms	The algebraic relationship between a dependent variable and explanatory variables
multiplicative form	Relationship where the dependent variable is a product of the explanatory variables
base tariff cell	The chosen set of rating categories where the rate equals the intercept of the model (the base value)
relativities	A numerical estimate of value in one category relative to the value in a base classification, typically expressed as a factor

non-automobile vehicles	Motorized vehicles which are not autos, such as atvs, off-road vehicles, go-carts, etc.
distributional structure	The manner in which a statistical distribution is parameterized
information matrix	Matrix that measures the amount of information that an observable random variable x carries about an unknown parameter of a distribution, and is used to calculate covariance matrices of maximum likelihood estimators
classification rating plan	A rating plan that uses an insured's risk characteristics to determine premium
credibility weight	The weight assigned to an insured's historical loss experience for the purposes of determining their premium in an experience rating plan
complement of credibility	The remainder of the weight not assigned to an insured's historical loss experience in the experience rating plan
class rate	Average rate per exposure for an insured in a particular classification group
full credibility standard	The threshold of experience necessary to assign 100% credibility to the insured's own experience
limited fluctuation credibility	A credibility method that attempts to limit fluctuations in its estimates
cumulative distribution function of the standard normal	Cumulative density function for the normal distribution with mean 0 and standard deviation 1
buhlmann credibility	A credibility method that uses the amount of experience, expected value of the process variance, and variance of the hypothetical means to determine the credibility weight
collective mean	The mean estimate of a risk when no loss information about the risk is known
law of total expectation	The expected value of the conditional expected value of x given y is the same as the expected value of x
risk parameter	Parameter in a distribution whose value reflects the risk categorization
expected value of the process variance	Average of the natural variability of observations from within each risk
variance of the hypothetical means	Variance of the means across different classes, used to determine how similar or different the classes are from one another
buhlmann-straub credibility	An extension of the buhlmann credibility model that allows for varying exposure by year
bayes theorem	A probability law that expresses conditional probability of the event a given the event b in terms of the conditional probability of the event b given the event a and the unconditional probability of a
bayesian inference	A branch of statistics that leverages bayes theorem to update the distribution as more experience becomes available

gamma-poisson model	A statistical model that assumes the frequency of claims is poisson whose mean has a prior distribution that is a gamma distribution
exact credibility	A situation where the bayesian credibility estimate matches that of the buhlmann credibility estimate
beta-binomial model	A statistical model for modeling the probability of an event using the binomial distribution with a probability that has a prior distribution from a beta distribution
nonparametric estimation	Statistical method that allows the functional form of a fit from data to have no assumed prior distribution, constraints, or parameters
empirical bayes methods	Credibility methods that estimate the credibility weight without using any assumptions about prior distributions or likelihoods, instead relying only on empirical data
semiparametric estimation	Credibility method that assumes a distribution for the loss per exposure random variable and otherwise uses empirical data
portfolios	A collection of contracts
insurance portfolios	A collection, or aggregation, of insurance contracts
reinsurers	A company that sells reinsurance
heavy tailed	A rv is said to be heavy tailed if high probabilities are assigned to large values
survival function	One minus the distribution function. it gives the probability that a rv exceeds a specific value.
coherent risk measure	A risk measure that is is subadditive, monontonic, has positive homogeneity, and is translation invariant.
mean excess loss function	The expected value of a loss in excess of a quantity, given that the loss exceeds the quantity
risk measure	A measure that summarizes the riskiness, or uncertainty, of a distribution
value-at-risk	A risk measure based on a quantile function
ceding company	A company that purchases reinsurance (also known as the reinsured)
excess of loss	Under an excess of loss arrangement, the insurer sets a retention level for each claim and pays claim amounts less than the level with the reinsurer paying the excess.
primary insurance	Insurance purchased by a non-insurer
proportional reinsurance	An agreement between a reinsurer and a ceding company (also known as the reinsured) in which the reinsurer assumes a given percent of losses and premium
quota share	A proportional treaty where the reinsurer receives a flat percent of the premium for the book of business reinsured and pays a percentage of losses, including allocated loss adjustment expenses. the reinsurer may also pays the ceding company a ceding commission which is designed to reflect the differences in underwriting expenses incurred.
reinsured	A company that purchases reinsurance (also known as the ceding company)

retained line	The amount of exposure that the the reinsured retains on a given line in a surplus share reinsurance agreement.
retention function	A function that maps the insurer portfolio loss into the amount of loss retained by the insurer.
stop-loss	Under a stop-loss arrangement, the insurer sets a retention level and pays in full total claims less than the level with the reinsurer paying the excess.
surplus share	A proportional reinsurance treaty that is common in commercial property insurance. a surplus share treaty allows the reinsured to limit its exposure on any one risk to a given amount (the retained line). the reinsurer assumes a part of the risk in proportion to the amount that the insured value exceeds the retained line, up to a given limit (expressed as a multiple of the retained line, or number of lines).
treaty	A reinsurance contract that applies to a designated book of business or exposures.
bonus-malus system	A type of rating mechanism where insured premiums are adjusted based on their individual loss experience history
no claim discount (ncd) system	A type of experience rating where insureds obtain discounts on future years' premiums based on claims-free experience
hunger for bonus	Phenomenon where insureds under an experience rating system are dissuaded from filing minor claims in order to keep their no-claims discount
takaful	Co-operative system of reimbursement or repayment in case of loss as an insurance alternative
markov chain	A stochastic model (time dependent) where the probability of each event depends only on the current state and not the historical path
transition matrix	Matrix that represents all probabilities for transition from one state to another (could be same state) for a markov chain
stationary distribution	Probability distribution remains unchanged in the markov chain as time progresses
ergodic	Irreducible markov chain where it is eventually possible to move from any state to any other state, with positive probability
irreversible	A markov chain where there does not exist a probability distribution that allows for the chain to be walked backwards in time
eigenvector	A non-zero vector that changes by only a scalar factor when that linear transformation is applied
n-step transition probability	Probability of ending in a state j after n periods, starting in state i, where i and j can be the same state
convergence rate	After n transitions, the sum of variation between the probability in each state vs. the stationary probability
poisson regression model	Type of regression model used for fitting data with an integral (count) response variable with mean equal to the variance

negative binomial regression model	Type of regression model used for fitting data with an integral (count) response variable and can account for variance greater than the mean
overdispersion	Phenomenon where the variance of data is larger than what is modeled
cross-classified rating classes	Table that combines the effects of multiple rating classifications
structured data	Data that can be organized into a repository format, typically a database
unstructured data	Data that is not in a predefined format, most notably text, audio visual
qualitative data	Data which is non numerical in nature
quantitative data	Data which is numerical in nature
ordinal data	Data field with a natural ordering
interval data	Continuous data which is broken into interval bands with a natural ordering
key-value databases	Data storage method that stores amd finds records using a unique key hash
column-oriented databases	Data storage method that stores records by column instead of by row
document databases	Data storage method that uses the document metadata for search and retrieval, also known as semi-structured data
data decay	Corruption of data due to hardware failure in the storage device
reverification	Manual process of checking the integrity of data
data element analysis	Analysis of the format and definition of each field
structural analysis	Statistical analysis of the structured data present to detect irregularities
robust	Statistics which are more unaffected by outliers or small departures from model assumptions
exploratory data analysis	Approach to analyzing data sets to summarize their main characteristics, using visual methods, descriptive statistics, clustering, dimension reduction
confirmatory data analysis	Process used to challenge assumptions about the data through hypothesis tests, significance testing, model estimation, prediction, confidence intervals, and inference
supervised learning methods	Model that predicts a response target variable using explanatory predictors as input
unsupervised learning methods	Models that work with explanatory variables only to describe patterns or groupings
classification methods	Supervised learning method where the response is a categorical variable
regression methods	Classical supervised learning method where the response may be continuous, binary, or a mixture of discrete and continuous

model flexibility	A measure of model complexity, typically based on the number of estimated parameters
explanatory modeling	Process where the modeling goal is to identify variables with meaningful and statistically significant relationships and test hypotheses
predictive modeling	Process where the modeling goal is to predict new observations
data modeling	Assumes data generated comes from a stochastic data model
algorithmic modeling	Assumes data generated comes from unknown algorithmic models
predictive accuracy	Quantitative measure of how well the explanatory variables predict the response outcome
scripts	A program or sequence of instructions that is executed by another program
reproducible analysis	Modeling practice where data, code, analyses are published together in a manner so that others may verify the findings
literate programming	Coding practice where documentation and code are written together
data ownership	Governance process that details legal ownership of enterprise-wide data and outlines who has ability to create, edit, modify, share and restrict access to the data
machine learning	Study of algorithms and statistical models that perform a specific task without using explicit instructions, relying on patterns and inference
pattern recognition	Automated recognition of patterns and regularities in data
data mining	Process of collecting, cleaning, processing, analyzing, and discovering patterns and useful insights from large data sets
principal component analysis	Dimension reduction technique that uses orthogonal transformations to convert a set of possibly correlated variables into a set of linearly uncorrelated variables
cluster analysis	Unsupervised learning method that aims to splot data into homogenous groups using a similarity measure
k-means algorithm	Type of clustering that aims to partition data into k mutually exclusive clusters by assigning observations to the cluster with the nearest centroid
linear regression	Supervised model that uses a linear function to approximate the relationship between the target and explanatory variables
generalized linear model	Supervised model that generalizes linear regression by allowing the linear component to be related to the response variable via a link function and by allowing the variance of each measurement to be a function of its predicted value
systematic component	The linear combination of explanatory variables component in a glm
link function	Function that relates between the linear predictor component to the mean of the target variable
decision trees	Modeling technique that uses a tree-like model of decisions to divide the sample space into non-overlapping regions to make predictions

categorical variable	A variable whose values are qualitative groups and can have no natural ordering (nominal) or an ordering (ordinal)
variables	A variable is any characteristics, number, or quantity that can be measured or counted.
interval variable	An ordinal variable with the additional property that the magnitudes of the differences between two values are meaningful
spatial data	Data and information having an implicit or explicit association with a location relative to the earth
high dimensional	Data set is high dimensional when it has many variables. In many applications, the number of variables may be larger than the sample size.
qualitative	This is a type of variable in which the measurement denotes membership in a set of groups, or categories
nominal variable	This is a type of qualitative/ categorical variable which has two or more categories without having any kind of natural order.
ordinal variable	This is a type of qualitative/ categorical variable which has two or more ordered categories.
binary variable	Is a special type of categorical variable where there are only two categories.
quantitative variable	A quantitative variable is a type of variable in which numerical level is a realization from some scale so that the distance between any two levels of the scale takes on meaning.
continuous variable	A continuous variable is a quantitative variable that can take on any value within a finite interval.
policyholder	Person in actual possession of insurance policy; policy owner.
discrete variable	A discrete variable is quantitative variable that takes on only a finite number of values in any finite interval.
count variable	A count variable is a discrete variable with values on nonnegative integers.
circular data	In a circular data, all values around the circle are equally likely. Example, imagine an analog picture of a clock.
insurers	An insurance company authorized to write insurance under the laws of any state.
multivariate	Multivariate variable involves taking many measurements on a single entity.
workers compensation	Insurance that covers an employer's liability for injuries, disability or death to persons in their employment, without regard to fault, as prescribed by state or federal workers' compensation laws and other statutes.
univariate	Univariate analysis is the simplest form of analyzing data. "Uni" means "one", so in other words your data has only one variable.

missing data	Missing data occur when no data value is stored for a variable in an observation. Missing data can occur because of nonresponse: no information is provided for one or more items or for a whole unit or subject.
censored	Censored data have unknown values beyond a bound on either end of the number line or both. Here, the data is observed but the values (measurements) are not known completely.
truncated	Truncation occurs when values beyond a boundary are either excluded when gathered or excluded when analyzed. An object can be detected only if its value is greater than some number.
stochastic process	Stochastic process is defined as a collection of random variables that is indexed by some mathematical set, meaning that each random variable of the stochastic process is uniquely associated with an element in the set.
deductibles	A deductible is a parameter specified in the contract. Typically, losses below the deductible are paid by the policyholder whereas losses in excess of the deductible are the insurer's responsibility (subject to policy limits and coninsurance).
rank based measures	Statistical dependence between the rankings of two variables
odds ratio	A statistic quantifying the strength of the association between two events, a and b, which is defined as the ratio of the odds of a in the presence of b and the odds of a in the absence of b
likelihood ratio test	A statistical test of the goodness-of-fit between two models
pearson correlation	A measure of the linear correlation between two variables
product-moment (pearson) correlation	Pearson correlation, a measure of the linear correlation between two variables
kendall tau	A statistic used to measure the ordinal association between two measured quantities
concordant	An observation pair (x,y) is said to be concordant if the observation with a larger value of x has also the larger value of y
discordant	An observation pair (x,y) is said to be discordant if the observation with a larger value of x has the smaller value of y
pearson chi-square statistic	A statistical test applied to sets of categorical data to evaluate how likely it is that any observed difference between the sets arose by chance
tetrachoric correlation	A technique for estimating the correlation between two theorised normally distributed continuous latent variables, from two observed binary variables
polychoric correlation	A technique for estimating the correlation between two theorised normally distributed continuous latent variables, from two observed ordinal variables
polyserial correlation	The correlation between two continuous variables with a bivariate normal distribution, where one variable is observed directly, and the other is unobserved

biserial correlation	A correlation coefficient used when one variable is dichotomous
normal score	Transformed data which closely resemble a standard normal distribution
copula	A multivariate distribution function with uniform marginals
spearmans rho	A nonparametric measure of rank correlation
marginal distributions	The probability distribution of the variables contained in the subset of a collection of random variables
fat-tailed	A fat-tailed distribution is a probability distribution that exhibits a large skewness or kurtosis, relative to that of either a normal distribution or an exponential distribution
probability integral transformation	Any continuous variable can be mapped to a uniform random variable via its distribution function
elliptical copulas	The copulas of elliptical distributions
correlation matrix	A table showing correlation coefficients between variables
elliptical distributions	Any member of a broad family of probability distributions that generalize the multivariate normal distribution
tail dependency	A measure of their comovements in the tails of the distributions
frechet-hoeffding bounds	Bounds of multivariate distribution functions
blomqvists beta	A dependence measure based on the center of the distribution
reinsurance	Insurance purchased by an insurer
deductible	A deductible is a parameter specified in the contract. typically, losses below the deductible are paid by the policyholder whereas losses in excess of the deductible are the insurer's responsibility (subject to policy limits and coninsurance).
coinsurance	Coinsurance is an arrangement whereby the insured and insurer share the covered losses. typically, a coinsurance parameter specified means that both parties receive a proportional share, e.g., 50%, of the loss.
pure premium	Pure premium is the total severity divided by the number of claims. it does not include insurance company expenses, premium taxes, contingencies, nor an allowance for profits. also called loss costs. some definitions include allocated loss adjustment expenses (alae).
standard deviation	The square-root of variance
variance	Second central moment of a random variable x, measuring the expected squared deviation of between the variable and its mean
aggregate claims	The sum of all claims observed in a period of time
median	50th percentile of a definition, or middle value where half of the distribution lies below
lorenz curve	A graph of the proportion of a population on the horizontal axis and a distribution function of interest on the vertical axis.
law of total variance	A decomposition of the variance of a random variable into conditional components. specifically, for random variables x and y on the same probability space, $\mathrm{var}(x) = e[\mathrm{var}(y\|x)] + \mathrm{var}[e(x\|y)]$.

tail value-at-risk	The expected value of a risk given that the risk exceeds a value-at-risk
coefficient of variation	Standard deviation divided by the mean of a distribution, to measure variability in terms of units of the mean
loss ratio	The sum of losses divided by the premium.
homogeneous risks	Risks that have the same distribution, that is, the distributions are identical.
heterogeneous	Heterogeneous risks have different distributions. often, we can attribute differences to varying exposures or risk factors.
exposure	A type of rating variable that is so important that premiums and losses are often quoted on a ”per exposure” basis. that is, premiums and losses are commonly standardized by exposure variables.
loss	The amount of damages sustained by an individual or corporation, typically as the result of an insurable event.
iid	Independent and identically distributed
pdf	Probability density function
aic	Akaike’s information criterion
bic	Bayesian information criterion
pmf	Probability mass function
mcmc	Markov Chain Monte Carlo
cdf	Cumulative distribution function
df	Degrees of freedom
glm	Generalized linear model
mle	Maximum likelihood estimate
ols	Ordinary least squares
pf	Probability function
rv	Random variable
reporting delay	The time that elapses between the occurrence of the insured event and the reporting of this event to the insurance company.
settlement delay	The time between reporting and settlement of a claim.
rbns	Reported, But is Not fully Settled
ibnr	Incurred in the past But is Not yet Reported. For such a claim the insured event took place, but the insurance company is not yet aware of the associated claim.
granular	
case estimates	The claims handlers expert estimate of the outstanding amount on a claim.
.csv	Comma separated value file
.txt	Text file
run-off triangle	Triangular display of loss reserve data. Accident or occurrence periods on one axis (often vertical) with development periods on the other (often horizontal). Also known as a development triangle.

development triangle	Triangular display of loss reserve data. Accident or occurrence periods on one axis (often vertical) with development periods on the other (often horizontal). Also known as a run-off triangle.
msep	Mean Squared Error of Prediction
chain-ladder method	An algorithm for predicting incomplete losses to their ultimate cumulative value. The name refers to the chaining of a sequence of (year-to-year development) factors into a ladder of factors.
wls	weighted least squares
glm	Generalized linear model

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